STIC Search Report
EIC 2100

USPTO

STIC Database Tracking Number: 152981

TO: Michael B Holmes
Location: RND 5A44
Art Unit: 2121
Thursday, June 02, 2005

Case Serial Number: 10/056438

From: Emory Damron
Location: EIC 2100
RND 4B19
Phone: 571-272-3520

Emory.Damron@uspto.gov

Search Notes

Dear Michael,

Please find below an inventor search in the bibliographic and full-text foreign patent files, as well as keyword searches in the patent and non-patent literature files, both bibliographic and full text.
References of potential pertinence have been tagged, but please review all the packets in case you like something I didn't.
Of those references which have been tagged, please note any manual highlighting which I've done within the document.
In addition to searching on Dialog, I also searched EPO/JPO/Derwent.
There may be a few decent references contained herein, but I'll let you determine how useful they may be to you.
Please contact me if I can refocus or expand any aspect of this case, and please take a moment to provide any feedback (on the form provided) so EIC 2100 may better serve your needs. Good Luck!

Sincerely,
Emory Damron
Technical Information Specialist
EIC 2100, US Patent & Trademark Office
Phone: (571) 272-3520
Emory.damron@uspto.gov

sira
Search and Information Resources Administration

```
Set     Items   Description
S1    1694745   IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT-
             ()(MAP OR MAPS OR MAPPED OR MAPPING)
S2     468841   SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO-
             RIAL? OR XRAY? OR X()(RAY OR RAYS OR RAYED OR RAYING)
S3     418753   PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON()EMISS-
             ION? OR MAGNETIC?()RESONANC? OR MRI
S4      18245   TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT)()SCAN? -
             OR CTSCAN?
S5    1316288   COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6     589117   DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO
             OR DATA OR CENTRAL)()PROCESS?
S7     128360   PROCESS?(2N)(MODULE? OR UNIT?)
S8        272   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S9      10617   MACHINE?(2N)LEARN? OR MACHINE()VECTOR? OR NEURAL()NETWORK?
             OR ARTIFICIAL()(NEURAL? OR INTELLIGEN?) OR BACK()PROPAGAT? OR
             OPTIM?()(HYPERPLAN? OR HYPER()PLAN?) OR CYBERNET?
S10     42856   PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF-
             ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?)(2W)PROCESS?
S11    133956   IDENTIF?(3N)(MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR
             TRANSCOD? OR DATA(3N)(MODIF? OR CONVERT? OR CONVERSION? OR AL-
             TER? OR CHANGE? OR CHANGING)
S12      6828   TRANSFORM? ?(3N)(RADON OR HOUGH) OR PRECLASSIF? OR PRE()(P-
             ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13    370669   TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG-
             HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14   2755893   ANALYS? OR ANALYZ? OR TEST??? OR DETECT?
S15   1582979   MONITOR? OR GAUG? OR RATE? OR RATING? OR SAMPLE? OR SAMPLI-
             NG?
S16    263856   EXAMIN? OR EVALUAT? OR ASCERTAIN? OR ASSESS?
S17    672589   KNOWN? OR TEMPLAT? OR STENCIL? OR STANDARD? ? OR NORM? ? OR
              PAR OR PROFILE?
S18   3367767   CONTROL OR CRITER? OR TOUCHSTONE? OR BENCHMARK? OR YARDSTI-
             CK? OR IDEAL? ? OR PARAGON? ?
S19   4103162   CLASSIF? OR SUBCLASSIF? OR SYSTEM? OR SUBSYSTEM? OR FEATUR-
             E? OR SUBFEATUR? OR CHARACTERISTIC? OR SUBCHARACTERISTIC?
S20   2367018   ATTRIBUT? OR SUBATTRIBUT? OR SEGMENT? OR SUBSEGMENT? OR CL-
             ASS?? OR SUBCLASS?? OR SECTION? OR SUBSECTION?
S21    340367   INDEX? OR SUBINDEX? OR CATEGOR? OR SUBCATEGOR? OR SUBDIVI?
             OR DIVISION?
S22   4735702   SET OR SETS OR RESULT? OR OUTPUT? OR PROCESS?()DATA
S23    899459   REALTIME? OR REAL()TIME? OR RTOS OR SYNCHRON? OR SIMULTAN?
             OR CONTEMPORAN? OR LIVE
S24   2127692   IC=(G06F? OR G06E? OR G06K? OR G06T? OR H04N?)
S25      1138   S1:S4 AND S5:S7 AND S8:S9
S26       112   S25 AND S10:S12
S27       651   S25 AND S13:S16 AND S17:S21
S28       282   S25 AND S5:S7(10N)S10:S16
S29       230   S27 AND S28
S30       693   S27:S29 AND S19:S24
S31       227   S29 AND S30
S32        19   S31 AND S23 AND S24
S33        89   S31 AND S17:S18
S34        80   S26 AND S27:S31
S35        41   S25 AND S22(10N)S13:S16 AND S22(10N)S17:S18
S36        36   S25 AND S23(10N)S10:S16
S37       237   S26 OR S32:S36
S38    808852   PR=2000:2005
S39       223   S37 NOT S38
S40       223   IDPAT (sorted in duplicate/non-duplicate order)
? show files
```

```
File 347:JAPIO Nov 1976-2005/Jan(Updated 050506)
         (c) 2005 JPO & JAPIO
File 350:Derwent WPIX 1963-2005/UD,UM &UP=200534
         (c) 2005  Thomson Derwent
?
```

40/3,K/1 (Item 1 from file: 350)
DIALOG(R)File 350:Derwent WPIX

012156452 **Image available**
WPI Acc No: 1998-573364/199849
XRPX Acc No: N98-446536

Digital image **processing using** neural network **interface - involves preconditioning initial** image data **through** image **concentration** conversion **module employing memory based** conversion **functions routing conditional** data **into** neural network **based** image **processor**

Patent Assignee: HITACHI MEDICAL CORP (HITR)
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 10255035	A	19980925	JP 9755780	A	19970311	199849	B

Priority Applications (No Type Date): JP 9755780 A 19970311
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 10255035	A		11	G06T-005/00	

Digital image **processing using** neural network **interface...**

...involves preconditioning initial image data **through** image **concentration** conversion **module employing memory based** conversion **functions routing conditional** data **into** neural network **based** image **processor**

...Abstract (Basic): The **digital image** processing employs a **neural network** based processor (2) to handle the initial **image** data input into the feed **module** (1). The **processed** data are delivered to a display device (3) for **analysis** . The **neural network** consists of the **standard** multilayer feed forward arrangement with **teacher** signal aided **training** and readjustment provisions for the individual weights associated with each neuron...

...Between the **neural network** based processor and the feed module, is positioned the **image** concentration conversion module (4) consisting of the serially connected multiplier and adder sub- modules served by memory based conversion functions. Provision exists to effect an inverse concentration correction on the **processed data** available from the **neural network** based processor. This inverse correction procedure employs serially positioned divider and subtractor sub-modules related...

...USE - In medical diagnostic and industrial **imaging** , consumer **photographic** applications...

Title Terms: **DIGITAL** ;
International Patent Class (Main): **G06T-005/00**
International Patent Class (Additional): **G06F-015/18** ...

... **G06T-001/00**

40/3,K/21 (Item 21 from file: 350)
DIALOG(R)File 350:Derwent WPIX

009293277 **Image available**
WPI Acc No: 1992-420687/199251
XRPX Acc No: N92-320864
Pre - processing **in detecting subject** image **area on radiographic recorded sheet - adds framing pixels to boundary of** image **pixel data and inputs resulting data to** neural network **to produce** binary **-coded data NoAbstract**
Patent Assignee: FUJI PHOTO FILM CO LTD (FUJF)
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 4317263	A	19921109	JP 9185579	A	19910417	199251	B

Priority Applications (No Type Date): JP 9185579 A 19910417
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 4317263	A		12	H04N-001/40	

Pre - processing **in detecting subject** image **area on radiographic recorded sheet...**
...adds framing pixels to boundary of image **pixel data and inputs resulting data to** neural network **to produce** binary **-coded data NoAbstract**
...Title Terms: **IMAGE** ;

40/3,K/53 (Item 53 from file: 350)
DIALOG(R)File 350:Derwent WPIX

014253589 **Image available**
WPI Acc No: 2002-074289/200210
Related WPI Acc No: 1999-302216
XRPX Acc No: N02-054774

Pattern recognition method for data clustering analysis in machine vision, involves assigning test data point to unambiguous class if test data point groups with several classes or no classes present in training set

Patent Assignee: SANDIA CORP (SAND-N)
Inventor: MARTINEZ R F; OSBOURN G C
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 6304675	B1	20011016	US 93174548	A	19931228	200210	B

Priority Applications (No Type Date): US 93174548 A 19931228
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 6304675	B1		31	G06K-009/62	

... **unambiguous class if test data point groups with several classes or no classes present in** training set

THREE RELATED DOX BENEATH

Abstract (Basic):

... Each of the **test** data points and **training** data points of respective data **sets** are selected and placed on each of the two specified positions of a region of...

...or if the test point groups with several classes or no class present in a **training set** .

... An INDEPENDENT CLAIM is also included for **training** data **set** quality verification method...

...Used for data clustering analysis used in machine vision, pattern recognition, unsupervised and supervised **machine learning** /classification, medical and biological **image** and data analysis, crop identification from satellite photos, identification of hazardous chemicals in complex environments...

...Enables successfully clustering complex data **sets** by assigning **test** data point to unambiguous class of the **training** data points. Enables achieving human-like judgment for class membership for n-dimensional test points, and the psychophysical-derived inhibitory **template** applied to the data **sets** enables the clustering performance. The need of operator-adjustable parameters or extensive neural net training...

...influence circumscribed by the template of the clustering method and the block diagram of the **data processor** .

40/3,K/55 (Item 55 from file: 350)
DIALOG(R)File 350:Derwent WPIX

013997999 **Image available**
WPI Acc No: 2001-482214/200152
XRPX Acc No: N01-356909

Automatic digitized mammogram analyzing **method for** detecting **possible cancerous tissue mass, involves** detecting **region of interest using** digitized mammogram **and Fourier spatial bandpass** analysis

Patent Assignee: LOCKHEED MARTIN CORP (LOCK)
Inventor: OLIVER D R; SHAPIRO G L
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US 6246782	B1	20010612	US 97870709	A	19970606	200152	B

Priority Applications (No Type Date): US 97870709 A 19970606
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US 6246782	B1		15	G06K-009/00	

Automatic digitized mammogram analyzing **method for** detecting **possible cancerous tissue mass, involves** detecting **region of interest using** digitized mammogram **and Fourier spatial bandpass** analysis

Abstract (Basic):

... The region of interest (ROI) is **detected** using a **digitized mammogram** and Fourier spatial bandpass **analysis** . The spatially bandpassed **images** of different resolutions of the **mammogram** , are used to identify brightest peak of the ROI, relative to the cancerous mass. Context data with ROI **attribute** information, is extracted from the **mammogram** . **Neural network trained** for the **attributes** of cancerous tissue region, generates **output** indicating if cancerous tissue mass is present in ROI.

... An INDEPENDENT CLAIM is also included for the automated cancerous mass **detection system** .

...

...For **detecting** cancer or other types of lesions in chest **X - ray** film, or cancerous and pre-cancerous cells in a pap smear or biopsy...

...Hybrid optical **digital computer** approach ensures sufficient processing power at moderate cost, to accommodate discriminating algorithms, and effective processing speed in **real - time** applications. The **system** performance such as sensitivity and specificity, is improved in the **real - time** .

...

...The figure shows the simplified block diagram of the automatic cancerous mass **detection system** .

...Title Terms: **DETECT** ;
International Patent Class (Main): **G06K-009/00**

40/3,K/58 **(Item 58 from file: 350)**
DIALOG(R)File 350:Derwent WPIX

LATE DATE

013733889 **Image available**
WPI Acc No: 2001-218119/200122
XRPX Acc No: N01-155507
Defect analysis **using** computer imaging **for use in production line, involves comparing divided sub-** images **of original** image **with** template **pattern, to determine defect**
Patent Assignee: IMAGING TECHNOLOGY INC (IMAG-N); ISRANI R G (ISRA-I); MELIKIAN S H (MELI-I); CORECO IMAGING INC (CORE-N)
Inventor: ISRANI R G; MELIKIAN S H
Number of Countries: 093 Number of Patents: 005
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
WO 200077720	A1	20001221	WO 2000US16662	A	20000616	200122	B
AU 200054952	A	20010102	AU 200054952	A	20000616	200122	
US 6477275	B1	20021105	US 99333701	A	19990616	200276	
US 20030002740	A1	20030102	US 99333701	A	19990616	200305	
			US 2002154459	A	20020523		
US 6636634	B2	20031021	US 99333701	A	19990616	200370	
			US 2002154459	A	20020523		

Priority Applications (No Type Date): US 99333701 A 19990616; US 2002154459 A 20020523

FIVE RELATED DOC BENEATH

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
WO 200077720	A1	E	28	G06K-009/64	

Designated States (National): AE AG AL AM AT AU AZ BA BB BG BR BY CA CH CN CR CU CZ DE DK DM DZ EE ES FI GB GD GE GH GM HR HU ID IL IN IS JP KE KG KP KR KZ LC LK LR LS LT LU LV MA MD MG MK MN MW MX NO NZ PL PT RO RU SD SE SG SI SK SL TJ TM TR TT TZ UA UG UZ VN YU ZA ZW
Designated States (Regional): AT BE CH CY DE DK EA ES FI FR GB GH GM GR IE IT KE LS LU MC MW MZ NL OA PT SD SE SL SZ TZ UG ZW

Patent No	Kind	Main IPC	Filing Notes
AU 200054952	A		Based on patent WO 200077720
US 6477275	B1	G06K-009/00	
US 20030002740	A1	G06K-009/64	Cont of application US 99333701
			Cont of patent US 6477275
US 6636634	B2	G06K-009/64	Cont of application US 99333701
			Cont of patent US 6477275

Defect analysis **using** computer imaging **for use in production line, involves comparing divided sub-** images **of original** image **with** template **pattern, to determine defect**

ALL LATE DATES — FEEL FREE TO DISREGARD

Abstract (Basic):
... The original object **image** is divided into a number of sub- **images** . Each sub- **image** is compared with a prestored **template** pattern, to generate score signals each representing the location of patterns in the **image** , determined as a function of respective sub- **images** . The score signals are processed using **artificial intelligence** grouping process, to determine the defect.
... a) Defect **analysis** **system** ;
(...

...b) Defect **analysis** program...

...For **detecting** defect in production line e.g. for use in assembly and inspection of electronic components soldered on **computer** board...

....More accurate representation of the **image** is enabled by the **image** sub-dividing process...

...The figure shows the **system** for locating a pattern within an **image** .

...Title Terms: **ANALYSE** ;
International Patent Class (Main): **G06K-009/00** ...

... **G06K-009/64**
International Patent Class (Additional): **G06K-005/00** ...

... **G06K-009/68** ...

... **G06T**-007/00 ...

... **H04N-007/18**

40/3,K/94   (Item 94 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010725173   **Image available**
WPI Acc No: 1996-222128/199622
Related WPI Acc No: 1997-145906
XRAM Acc No: C96-070542
XRPX Acc No: N96-186377

Computer **-assisted method for diagnosing diseases e.g. cancer and osteoporosis - measures concns. of bio-markers, digitises values and introduces them to** trained neural network **whose** output **indicates presence or absence of disease**

Patent Assignee: HORUS THERAPEUTICS INC (HORU-N)
Inventor: BARNHILL S D; ZHANG Z
Number of Countries: 019 Number of Patents: 002
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
WO 9612187	A1	19960425	WO 95US1379	A	19950202	199622	B
AU 9518374	A	19960506	AU 9518374	A	19950202	199636	

Priority Applications (No Type Date): US 94323446 A 19941013
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
WO 9612187	A1	E	88	G01N-033/53	
AU 9518374	A			G01N-033/53	Based on patent WO 9612187

WO 9612187 Designated States (National): AU CA JP
WO 9612187 Designated States (Regional): AT BE CH DE DK ES FR GB GR IE IT LU MC NL PT SE

THREE RELATED DOCS, BENEATH

Computer **-assisted method for diagnosing diseases e.g. cancer and osteoporosis...**

...measures concns. of bio-markers, digitises values and introduces them to trained neural network **whose** output **indicates presence or absence of disease**

...Abstract (Basic): Diagnosis of disease in a human or animal comprises measuring the concns. of a predetermined **set** of bio-markers **known** to be associated with the disease from a biological fluid. The **digitised** values of the concns. are scaled and introduced to a trained **neural network** . **Output** values from the network tend towards an upper value when the disease is present and...

...The method is sensitive and does not expose the patient to unnecessary radiation, e.g. **X - rays** . The **neural network** can discern patterns and trends too subtle or complex for humans or computational methods to ...

Title Terms: **COMPUTER0** ;
...International Patent Class (Additional): **G06F-159/00**

40/3,K/101 (Item 101 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010456985 **Image available**
WPI Acc No: 1995-358304/199546
Related WPI Acc No: 1993-311977
XRPX Acc No: N95-266307
Person identifying system **using** neural network **- matches extracted data** feature **of input data with recorded data during** evaluation **by** artificial neural network
Patent Assignee: US DEPT OF THE NAVY (USNA)
Inventor: COOPER P; FARSAIE A; KINZER D G
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US N8322653	N	19950901	US 9328012	A	19930308	199546	B
			US 94322653	A	19941011		

Priority Applications (No Type Date): US 94322653 A 19941011; US 9328012 A 19930308
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US N8322653	N		10	G06K-000/00	CIP of application US 9328012

Person identifying system **using** neural network **- ...**
...matches extracted data feature **of input data with recorded data during** evaluation **by** artificial neural network

...Abstract (Basic): The **system** (10) senses person identifying **features** , extracted from e.g. a **photograph** , voice pattern, fingerprint and PIN personal identification number. It **digitises** , **preprocesses** (14) and stores the acquired data. **Sets** of numerical values are extracted (16) from the data and processed by the **artificial neural network** (18) for **evaluation** .
...

...The **neural network** forms a **training set** to process the extracted data during a **training** phase. It compares between mass centres and neuron centres adjusted to represent data. **Features** identifying a person are determined and **classified** . The **neural network** provides inputs for the person recognition readout (20) and feedback for the **preprocessing** and **feature** extraction. Hence its operation is adjusted in response to variations in the **preprocessing** and **feature** extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses **artificial neural network** -based **system** so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few **features** .
...

...The **system** (10) senses person identifying **features** , extracted from e.g. a **photograph** , voice pattern, fingerprint and PIN personal identification number. It **digitises** , **preprocesses** (14) and stores the acquired data. **Sets** of numerical values are extracted (16) from the data and processed by the **artificial neural network** (18) for **evaluation** .

...

...The **neural network** forms a **training set** to process the extracted data during a **training** phase. It compares between mass centres and neuron centres adjusted to represent data. **Features** identifying a person are determined and **classified** . The 1neural network provides inputs for the person recognition readout (20) and feedback for the **preprocessing** and **feature** extraction. Hence its operation is adjusted in response to variations in the **preprocessing** and **feature** extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses **artificial neural network** -based **system** so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few **features** .

...

...The **system** (10) senses person identifying **features** , extracted from e.g. a **photograph** , voice pattern, fingerprint and PIN personal identification number. It **digitises** , **preprocesses** (14) and stores the acquired data. **Sets** of numerical values are extracted (16) from the data and processed by the **artificial neural network** (18) for **evaluation** .

...

...The **neural network** forms a **training set** to process the extracted data during a **training** phase. It compares between mass centres and neuron centres adjusted to represent data. **Features** identifying a person are determined and **classified** . The **neural network** provides inputs for the person recognition readout (20) and feedback for the **preprocessing** and **feature** extraction. Hence its operation is adjusted in response to variations in the **preprocessing** and **feature** extraction...

...USE/ADVANTAGE - For automatic teller machine in bank. Reduced computational complexity as uses **artificial neural network** -based **system** so rapid and accurate recognition. Non-algorithmic method to adaptively cluster data on people from few **features** .

...Title Terms: **SYSTEM** ;

International Patent Class (Main): **G06K-000/00**

40/3,K/104 (Item 104 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010199553 **Image available**
WPI Acc No: 1995-100807/199514
XRPX Acc No: N96-088966
Micro-calcification detecting **method used in diagnosing cancer - involves converting interested area of** digital **breast** X - ray image **into** digital **data and inputting data in** neural network **NoAbstract**
Patent Assignee: ARCH DEV CORP (ARCH-N)
Inventor: DOI K; ZHANG W
Number of Countries: 002 Number of Patents: 002
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
JP 6343627	A	19941220	JP 9497365	A	19940511	199514	B
US 5491627	A	19960213	US 9360531	A	19930513	199612	

Priority Applications (No Type Date): US 9360531 A 19930513
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
JP 6343627	A		25		
US 5491627	A		30		

Micro-calcification detecting **method used in diagnosing cancer...**
...involves converting interested area of digital **breast** X - ray image **into** digital **data and inputting data in** neural network **NoAbstract**

RELATED
Doc. Bernstein

...Abstract (Basic): The method involves obtaining a **digital mammogram** and...

...extracting regions of interest from the **mammogram** suspected of containing a microcalcification. Regions of interest are **converted** into corresponding numerical **data** . The numerical data is input into a shift-invariant **neural network trained** to **detect** microcalcifications for processing. The **neural network** produces corresponding **output images** .

...

...A microcalcification in the **digital mammogram** is **detected** using the **output images** . Extracting the regions of interest involves extracting regions suspected of containing a clustered microcalcification. This in turn involves selecting regions containing false-positive **microcalcifications** . **Processing** by the **neural network** includes removing a portion of the false-positive microcalcifications selected in the extracting step...

...ADVANTAGE - Preserves true positive **detections** while lowering false ones. Uses regions of interest in the spatial domain to perform clustered microcalcification. Performs microcalcification **detection** independently of relative locations of microcalcifications and cluster orientation. Uses shift invariant **neural network** and **feature** extraction techniques to **detect** microcalcifications. Uses **feature** thresholding in addition to **neural network** to remove false positives

...Title Terms: **DETECT** ;

40/3,K/108 (Item 108 from file: 350)
DIALOG(R)File 350:Derwent WPIX

010067117 **Image available**
WPI Acc No: 1994-334830/199442
XRPX Acc No: N94-262934
Computer **implemented process of recognising** image **pattern among** set **of** known templates **- involves scanning** image , segmenting image **to** detect **pattern,** preprocessing detected **pattern and applying** preprocessed detected **pattern to** trained neural network
Patent Assignee: CANON KK (CANO)
Inventor: AVI-ITZHAK H I; DIEP T A; GARLAND H T; THAN A D
Number of Countries: 005 Number of Patents: 006
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
EP 622750	A2	19941102	EP 94303081	A	19940428	199442	B
EP 622750	A3	19950426	EP 94303081	A	19940428	199545	
US 5475768	A	19951212	US 9355523	A	19930429	199604	
US 5625707	A	19970429	US 9355523	A	19930429	199723	
			US 95445470	A	19950522		
EP 622750	B1	20000105	EP 94303081	A	19940428	200006	
DE 69422446	E	20000210	DE 622446	A	19940428	200015	
			EP 94303081	A	19940428		

Priority Applications (No Type Date): US 9355523 A 19930429; US 95445470 A 19950522

TWO RELATED DOCS, BENEATH

Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
EP 622750	A2	E	12	G06K-009/36	
Designated States (Regional): DE FR GB IT					
EP 622750	B1	E		G06K-009/36	
Designated States (Regional): DE FR GB IT					
DE 69422446	E			G06K-009/36	Based on patent EP 622750
US 5475768	A		11	G06K-009/66	
US 5625707	A		11	G06T-001/40	Div ex application US 9355523
					Div ex patent US 5475768
EP 622750	A3			G06K-009/36	

Computer **implemented process of recognising** image **pattern among** set **of** known templates - ...

...**involves scanning** image , segmenting image **to** detect **pattern,** preprocessing detected **pattern and applying** preprocessed detected **pattern to** trained neural network

...Abstract (Basic): The process involves scanning an **image** including a pattern to be recognised and **detecting** the pattern by **segmenting** the **image** . A **neural network** (108) is **trained** using the **set** of **known templates** . The **detected** pattern is **preprocessed** and the **preprocessed** pattern is applied to the **trained neural network** as input. The pattern is recognised as one of the **known templates** corresp. to an **output** of the **trained neural network** .
...

...The **detected** pattern is comprised of a number of pixels. **Preprocessing** involves filtering pixel values by selectively assigning a predetermined filtered pixel value to a subset...

...ADVANTAGE - **Neural network** based OCR **system** has high accuracy even for imperfect **images** .

...Abstract (Equivalent): A **computer** -implemented process of **training** a **neural network** , said process comprising...

...a) providing a plurality of **templates** , each **template** corresponding to a distinct **image** ; and...

...b) for each of the plurality of **templates** :

...

...defining a frame around the **template** ;

...

...determining a centroid of the **template** ;

...

...positioning the **template** within the frame such that the centroid is centrally located with respect to the frame...

...randomly displacing the **template** horizontally and vertically within the frame; and...

... **training** the **neural network** by applying the randomly displaced **template** to the **neural network** .

...

...A **computer** -implemented process of recognizing a pattern in an **image** among a **set** of **known templates** , the process comprising...

...a) **training** a **neural network** using said **set** of **known templates** ;

...

...b) scanning said **image** ; c) **detecting** said pattern by **segmenting** said scanned **image** into a **detected** pattern comprising a plurality of pixels, each such pixel having a value; d) **preprocessing** said **detected** pattern by: i) determining a minimum of said values of said pixels; ii) subtracting the...

...of said pixels in said subset not exceeding a threshold value; and e) recognizing said **preprocessed detected** pattern as corresponding to one of said **known templates** by applying said **preprocessed detected** pattern to said **trained neural network** .

Title Terms: **COMPUTER** ;
International Patent Class (Main): **G06K-009/36** ...

... **G06K-009/66** ...

... **G06T-001/40**

40/3,K/119 (Item 119 from file: 350)
DIALOG(R)File 350:Derwent WPIX

009618428 **Image available**
WPI Acc No: 1993-311977/199339
Related WPI Acc No: 1995-358304
XRPX Acc No: N93-240197

Feature **extraction technique for target recognition - sensing** image **scene from different viewing angles for** image **data acquisition, extracting** features **from data, and** evaluating **data in** artificial neural network **to identify target within** image **scene**

Patent Assignee: US DEPT OF THE NAVY (USNA)
Inventor: FARSAIE A; FULLER J J
Number of Countries: 001 Number of Patents: 001
Patent Family:

Patent No	Kind	Date	Applicat No	Kind	Date	Week	
US N8028012	N	19930915	US 9328012	A	19930308	199339	B

Priority Applications (No Type Date): US 9328012 A 19930308
Patent Details:

Patent No	Kind	Lan	Pg	Main IPC	Filing Notes
US N8028012	N		10	G06F-000/00	

Feature **extraction technique for target recognition...**

...**sensing** image **scene from different viewing angles for** image **data acquisition, extracting** features **from data, and** evaluating **data in** artificial neural network **to identify target within** image **scene**

...Abstract (Basic): method involves gathering input data relating to baseline targets within real environments, often having an **image** degrading **characteristic** , during an **image** acquisition phase (12). The gathered **image** data is then **digitised** and **pre - processed** (14) to eliminate extraneous data. Extraction of target **features** from such **pre - processed** **image** data is performed by **feature** extraction (16...

...The extracted **feature** data then undergoes **training** or **testing** procedures through an **artificial neural network** (18) in order to provide inputs for target recognition readout (20). The **output** of the **artificial neural network** also provides feedbacks for **preprocessing** and **feature** extraction. Operation of the **artificial neural network** is thereby adjusted in response to variations in the **preprocessing** of the input **image** data and **feature** extraction...

...ADVANTAGE - Reduces **training** time and computational complexity in **artificial neural network system** . Rapid and accurate recognition and identification of **image features** extracted from input **image** data...

...method involves gathering input data relating to baseline targets within real environments, often having an **image** degrading **characteristic** , during an **image** acquisition phase (12). The gathered **image** data is then **digitised** and **pre - processed** (14) to eliminate extraneous data. Extraction of target **features** from such **pre - processed** **image** data is performed by **feature** extraction (16...

...The extracted **feature** data then undergoes **training** or **testing** procedures through an **artificial neural network** (18) in order to provide inputs for target recognition readout (20). The **output** of the

artificial neural network also provides feedbacks for **preprocessing** and **feature** extraction. Operation of the **artificial neural network** is thereby adjusted in response to variations in the **preprocessing** of the input **image** data and **feature** extraction...

...ADVANTAGE - Reduces **training** time and computational complexity in **artificial neural network system** . Rapid and accurate recognition and identification of **image features** extracted from input **image** data...

...method involves gathering input data relating to baseline targets within real environments, often having an **image** degrading **characteristic** , during an **image** acquisition phase (12). The gathered **image** data is then **digitised** and **pre - processed** (14) to eliminate extraneous data. Extraction of target **features** from such **pre - processed image** data is performed by **feature** extraction (16...

...The extracted **feature** data then undergoes **training** or **testing** procedures through an **artificial neural network** (18) in order to provide inputs for target recognition readout (20). The **output** of the **artificial neural network** also provides feedbacks for **preprocessing** and **feature** extraction. Operation of the **artificial neural network** is thereby adjusted in response to variations in the **preprocessing** of the input **image** data and **feature** extraction...

...ADVANTAGE - Reduces **training** time and computational complexity in **artificial neural network system** . Rapid and accurate recognition and identification of **image features** extracted from input **image** data...

Title Terms: **FEATURE** ;

International Patent Class (Main): **G06F-000/00**

40/3,K/169 (Item 169 from file: 347)
DIALOG(R)File 347:JAPIO

04780729 **Image available**
METHOD AND DEVICE FOR PROCESSING **IMAGE**

PUB. NO.: 07-073329 [JP 7073329 A]
PUBLISHED: March 17, 1995 (19950317)
INVENTOR(s): TAN EE DEIEPU
HADAARU AI ABUIIITSUAAKU
HARII TEII GAARANDO
APPLICANT(s): CANON INC [000100] (A Japanese Company or Corporation), JP (Japan)
APPL. NO.: 06-092540 [JP 9492540]
FILED: April 28, 1994 (19940428)
PRIORITY: 7-55,523 [US 55523-1993], US (United States of America), April 29, 1993 (19930429)

THREE RELATED DOCS, BENSATH

METHOD AND DEVICE FOR PROCESSING **IMAGE**

INTL CLASS: **G06T-007/00 ; G06T-007/60 ; G06K-009/62**
...JAPIO CLASS: Input **Output** Units)
...JAPIO KEYWORD:Microcomputers & **Microprocessers**)

ABSTRACT
PURPOSE: To accurately recognize a pattern from the **image** having much noise by **learning** a **neural network** while using a **known template** pattern, performing the **preprocessing** of a **detected** pattern, and applying the **preprocessed** pattern to the **neural network** .

...

...CONSTITUTION: A **neural network** 108 is **learnt** by using the **known template** pattern. A scanner 102 is used for providing the two-dimensional arrangement of picture elements expressing a scanning **image** containing the pattern of a recognizing target. A **segment** 104 is **detected** by separating this pattern form the other **image** elements. A processor 106 performs the **preprocessing** of the **detected** pattern for facilitating pattern recognition. The **neural network** 108 receives the **detected preprocessed** pattern as an input and **outputs** a signal for expressing the recognized pattern. This **preprocessing** is composed of deciding the centroid of the pattern and positioning the centroid at the

40/3,K/219 (Item 219 from file: 347)
DIALOG(R)File 347:JAPIO

03566478 **Image available**
IMAGE SORTING/IDENTIFYING DEVICE

PUB. NO.: 03-229378 [JP 3229378 A]
PUBLISHED: October 11, 1991 (19911011)
INVENTOR(s): ISO TOSHIKI
KOSUGI MAKOTO
APPLICANT(s): NIPPON TELEGR & TELEPH CORP <NTT> [000422] (A Japanese Company or Corporation), JP (Japan)
APPL. NO.: 02-025699 [JP 9025699]
FILED: February 05, 1990 (19900205)
JOURNAL: Section: P, Section No. 1296, Vol. 16, No. 9, Pg. 105, January 10, 1992 (19920110)

IMAGE SORTING/IDENTIFYING DEVICE

INTL CLASS: **G06F-015/70** ; **G06F-015/18**
...JAPIO CLASS: **Computer** Applications)

ABSTRACT
PURPOSE: To sort and identify even the unknown **images** by combining the **neural networks** having the **learning** functions and capable of the nonlinear mapping in parallel to each other and in a...

...CONSTITUTION: A face **image** data input part 1 fetches the unknown face **image** data and sends this data to a **pre - processing** circuit 2. This circuit 2 extracts the **features** of each parts out of the face **image** data, i.e., the **output** of the part 1 and at the same time sorts the parts with the function which is previously **learnt** from various face **image** data. The **outputs** of these circuits 2 are collected in a main **neural network** 3 where the face **images** are sorted and identified by the function which is also previously **learnt** . Thus even the unknown face **images** can be sorted and identified.

```
Set      Items   Description
S1      606387   IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT-
                 ()(MAP OR MAPS OR MAPPED OR MAPPING)
S2      342282   SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO-
                 RIAL? OR XRAY? OR X()(RAY OR RAYS OR RAYED OR RAYING) OR RADI-
                 OGRA?
S3      108298   PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON()EMISS-
                 ION? OR MAGNETIC?()RESONANC? OR MRI
S4       15657   TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT)()SCAN? -
                 OR CTSCAN?
S5      516244   COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6      171956   DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO
                 OR DATA OR CENTRAL)()PROCESS?
S7      105910   PROCESS?(2N)(MODULE? OR UNIT?)
S8        1599   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S9       12510   MACHINE?(2N)LEARN? OR MACHINE()VECTOR? OR NEURAL()NETWORK?
                 OR ARTIFICIAL()(NEURAL? OR INTELLIGEN?) OR BACK()PROPAGAT? OR
                 OPTIM?()(HYPERPLAN? OR HYPER()PLAN?) OR CYBERNET?
S10      68366   PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF-
                 ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?)(2W)PROCESS?
S11     108252   IDENTIF?(3N)(MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR
                 TRANSCOD? OR DATA(3N)(MODIF? OR CONVERT? OR CONVERSION? OR AL-
                 TER? OR CHANGE? OR CHANGING)
S12      10407   TRANSFORM? ?(3N)(RADON OR HOUGH) OR PRECLASSIF? OR PRE()(P-
                 ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13     456274   TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG-
                 HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14     981173   ANALYS? OR ANALYZ? OR TEST??? OR DETECT?
S15     886381   MONITOR? OR GAUG? OR RATE? OR RATING? OR SAMPLE? OR SAMPLI-
                 NG?
S16    1837109   EXAMIN? OR EVALUAT? OR ASCERTAIN? OR ASSESS?
S17    1780715   KNOWN? OR TEMPLAT? OR STENCIL? OR STANDARD? ? OR NORM? ? OR
                  PAR OR PROFILE?
S18     967103   CONTROL OR CRITER? OR TOUCHSTONE? OR BENCHMARK? OR YARDSTI-
                 CK? OR IDEAL? ? OR PARAGON? ?
S19    1600114   CLASSIF? OR SUBCLASSIF? OR SYSTEM? OR SUBSYSTEM? OR FEATUR-
                 E? OR SUBFEATUR? OR CHARACTERISTIC? OR SUBCHARACTERISTIC?
S20    1086021   ATTRIBUT? OR SUBATTRIBUT? OR SEGMENT? OR SUBSEGMENT? OR CL-
                 ASS?? OR SUBCLASS?? OR SECTION? OR SUBSECTION?
S21     429565   INDEX? OR SUBINDEX? OR CATEGOR? OR SUBCATEGOR? OR SUBDIVI?
                 OR DIVISION?
S22    1491745   SET OR SETS OR RESULT? OR OUTPUT? OR PROCESS?()DATA
S23     579576   REALTIME? OR REAL()TIME? OR RTOS OR SYNCHRON? OR SIMULTAN?
                 OR CONTEMPORAN? OR LIVE
S24     235455   IC=(G06F? OR G06E? OR G06K? OR G06T? OR H04N?)
S25       2399   S1:S4(10N)S5:S7 AND S1:S7(20N)S8:S9
S26        787   S25 AND S10:S12(20N)S1:S7
S27        705   S26 AND S13 AND S14:S16
S28        703   S27 AND S13:S16(10N)S17:S22
S29        670   S28 AND S23:S24
S30        701   S28 AND S17:S18 AND S19:S21 AND S22
S31        668   S29 AND S30
S32        362   S31 AND S8:S9(10N)S13
S33        457   S31 AND S13(5N)(S22 OR DATA?) AND S14:S16(5N)(S22 OR DATA?)
S34        565   S31 AND S17:S18(5N)(S22 OR DATA?)
S35        411   S26:S31 AND S1:S4(5N)S5:S7(5N)S14:S16
S36        119   S35 AND S32 AND S33 AND S34
S37        336   S35 AND S32:S34
S38        234   S37 AND S24
S39        173   S37:S38 AND S1:S12/TI
? show files
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File 348:EUROPEAN PATENTS 1978-2005/May W03
        (c) 2005 European Patent Office
File 349:PCT FULLTEXT 1979-2005/UB=20050519,UT=20050512
        (c) 2005 WIPO/Univentio
?
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36/3/27 (Item 27 from file: 348)
DIALOG(R)File 348:EUROPEAN PATENTS

00626757
Application of neural networks as an aid in medical diagnosis and general anomaly detection.
Anwendung von Neuralnetzwerken als Hilfe fur die medizinische Diagnose und allgemeiner Nachweis von Anomalien.
Application de reseaux neuronaux pour aider dans le diagnostic medical et detection **generale d'anomalies.**
PATENT ASSIGNEE:
E.I. DU PONT DE NEMOURS AND COMPANY, (200580), 1007 Market Street, Wilmington Delaware 19898, (US), (applicant designated states: BE;DE;FR;GB)
INVENTOR:
Stafford, Richard Gordon, 6 Top of Oaks, Chadds Ford, Pennsylvania 19317, (US)
Mickewich, Daniel James, 2005 Millers Road, Arden, Delaware 19810, (US)
Beutel, Jacob, 614 Loverville Road, E-1B, Hockessin, Delaware 19707, (US)
LEGAL REPRESENTATIVE:
von Kreisler, Alek, Dipl.-Chem. et al (12437), Patentanwalte, von Kreisler-Selting-Werner, Bahnhofsvorplatz 1 (Deichmannhaus), 50667 Koln , (DE)
PATENT (CC, No, Kind, Date): EP 610805 A2 940817 (Basic)
EP 610805 A3 950607
APPLICATION (CC, No, Date): EP 94101600 940203;
PRIORITY (CC, No, Date): US 16343 930211
DESIGNATED STATES: BE; DE; FR; GB
INTERNATIONAL PATENT CLASS: **G06F-015/80 ; G06F-019/00**
ABSTRACT WORD COUNT: 93

Two related dox beneath

LANGUAGE (Publication,Procedural,Application): English; English; English
FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS A	(English)	EPABF2	450
SPEC A	(English)	EPABF2	4645
Total word count - document A			5095
Total word count - document B			0
Total word count - documents A + B			5095

36/3/113 (Item 78 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00365227
COMPUTER ASSISTED METHODS FOR DIAGNOSING DISEASES
PROCEDES DE DIAGNOSTIC DE MALADIES ASSISTE PAR ORDINATEUR
Patent Applicant/Assignee:
HORUS THERAPEUTICS INC,
Inventor(s):
BARNHILL Stephen M,
ZHANG Zhen,
Patent and Priority Information (Country, Number, Date):
Patent: WO 9705553 A1 19970213
Application: WO 96US12177 19960725 (PCT/WO US9612177)
Priority Application: US 951425 19950725; US 96642848 19960503
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AU CA CN JP NZ AT BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 16562

THESE RELATED DOX BENEATH

39/3/56 (Item 56 from file: 348)
DIALOG(R)File 348:EUROPEAN PATENTS

00473856
Computer-aided diagnosis system for medical use
Rechnergestutztes System zur Diagnose fur medizinischen Gebrauch
Systeme **assiste** par **ordinateur pour le diagnostic a usage medical**
PATENT ASSIGNEE:
KABUSHIKI KAISHA TOSHIBA, (213130), 72, Horikawa-cho, Saiwai-ku, Kawasaki-shi, Kanagawa-ken 210-8572, (JP), (Proprietor designated states: all)
INVENTOR:
Yamada, Shinichi, c/o Intellectual Property Div., Kabushiki Kaisha Toshiba, 1-1 Shibaura 1-chome, Minato-ku, Tokyo 105, (JP)
Komatsu, Kenichi, c/o Intellectual Property Div., Kabushiki Kaisha Toshiba, 1-1 Shibaura 1-chome, Minato-ku, Tokyo 105, (JP)
Ema, Takehiro, c/o Intellectual Property Div., Kabushiki Kaisha Toshiba, 1-1 Shibaura 1-chome, Minato-ku, Tokyo 105, (JP)
LEGAL REPRESENTATIVE:
Blumbach, Kramer & Partner GbR (101302), Radeckestrasse 43, 81245 Munchen , (DE)
PATENT (CC, No, Kind, Date): EP 487110 A2 920527 (Basic)
EP 487110 A3 930929
EP 487110 B1 991006
APPLICATION (CC, No, Date): EP 91119983 911122;
PRIORITY (CC, No, Date): JP 90320498 901122
DESIGNATED STATES: DE; NL
INTERNATIONAL PATENT CLASS: **G06F-019/00**
ABSTRACT WORD COUNT: 197
NOTE:
Figure number on first page: 1

FIVE RELATED DOCS, B2NZOTH

LANGUAGE (Publication,Procedural,Application): English; English; English
FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS B	(English)	9940	586
CLAIMS B	(German)	9940	589
CLAIMS B	(French)	9940	715
SPEC B	(English)	9940	13386
Total word count - document A			0
Total word count - document B			15276
Total word count - documents A + B			15276

39/3/60 (Item 60 from file: 348)
DIALOG(R)File 348:EUROPEAN PATENTS

00352006
Method and apparatus for adaptive learning type general purpose image measurement and recognition
Verfahren und Gerat fur universelle adaptiv lernende Bildmessung und -erkennung
Procede et dispositif de mesure et reconnaissance d' images **universelles avec apprentissage adaptatif**

PATENT ASSIGNEE:
  KABUSHIKI KAISHA OUYO KEISOKU KENKYUSHO, (807871), 3-26-12, Kita-Senzoku, Ohta-ku, Tokyo, (JP), (applicant designated states: DE;FR;GB;IT;SE)
  AGENCY OF INDUSTRIAL SCIENCE AND TECHNOLOGY, (213421), 3-1, Kasumigaseki 1-chome, Chiyoda-ku Tokyo, (JP), (applicant designated states: DE;FR;GB;IT;SE)
INVENTOR:
  Otsu, Nobuyuki, 1-1-4, Umezono, Tsukuba-Shi Ibaraki, (JP)
  Kurita, Takio, 1-1-4, Umezono, Tsukuba-Shi Ibaraki, (JP)
  Kuwashima, Shigesumi, 3-22-3, Kita-Senzoku Ohta-ku, Tokyo, (JP)
LEGAL REPRESENTATIVE:
  Klunker . Schmitt-Nilson . Hirsch (101001), Winzererstrasse 106, 80797 Munchen, (DE)
PATENT (CC, No, Kind, Date): EP 363828 A2 900418 (Basic)
                              EP 363828 A3 920812
                              EP 363828 B1 990107
APPLICATION (CC, No, Date): EP 89118529 891005;
PRIORITY (CC, No, Date): JP 88255678 881011; JP 88255679 881011
DESIGNATED STATES: DE; FR; GB; IT; SE
INTERNATIONAL PATENT CLASS: **G06K-009/52 ; G06K-009/62B**
ABSTRACT WORD COUNT: 206

TWO RELATED DOX BENEATH

LANGUAGE (Publication,Procedural,Application): English; English; English
FULLTEXT AVAILABILITY:

Available Text	Language	Update	Word Count
CLAIMS B	(English)	9901	679
CLAIMS B	(German)	9901	612
CLAIMS B	(French)	9901	726
SPEC B	(English)	9901	6260
Total word count - document A			0
Total word count - document B			8277
Total word count - documents A + B			8277

39/3/140 (Item 78 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00549760 **Image available**
METHOD AND SYSTEM FOR THE COMPUTERIZED ANALYSIS OF BONE MASS AND STRUCTURE
PROCEDE ET SYSTEME D'ANALYSE INFORMATISES DE LA MASSE ET DE LA STRUCTURE DE L'OS
Patent Applicant/Assignee:
ARCH DEVELOPMENT CORPORATION,
Inventor(s):
JIANG Chunsheng,
CHINANDER Michael R,
GIGER Maryellen L,
Patent and Priority Information (Country, Number, Date):
Patent: WO 200013133 A1 20000309 (WO 0013133)
Application: WO 99US18825 19990827 (PCT/WO US9918825)
Priority Application: US 98141535 19980828
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 19330

Two related dox. beneath

39/3/142 (Item 80 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00497502 **Image available**
METHOD AND SYSTEM FOR AUTOMATED MULTI-SAMPLED DETECTION OF LESIONS IN IMAGES
PROCEDE ET SYSTEME PERMETTANT DE DETECTER AUTOMATIQUEMENT AVEC PLUSIEURS ECHANTILLONS DES LESIONS DANS LES IMAGES
Patent Applicant/Assignee:
ARCH DEVELOPMENT CORPORATION,
Inventor(s):
NISHIKAWA Robert M,
DOI Kunio,
Patent and Priority Information (Country, Number, Date):
Patent: WO 9928854 A1 19990610
Application: WO 98US24932 19981125 (PCT/WO US9824932)
Priority Application: US 97979639 19971128
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 7564

FIVE RELATED DOCS, BREATH

39/3/147 (Item 85 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00473338 **Image available**
METHOD AND SYSTEM FOR THE AUTOMATED ANALYSIS OF LESIONS IN MAGNETIC RESONANCE IMAGES
PROCEDE ET SYSTEME D'ANALYSE AUTOMATIQUE DE LESIONS DANS DES IMAGES OBTENUES PAR RESONANCE MAGNETIQUE
Patent Applicant/Assignee:
ARCH DEVELOPMENT CORPORATION,
Inventor(s):
GILHUIJS Kenneth,
GIGER Maryellen L,
BICK Ulrich,
Patent and Priority Information (Country, Number, Date):
Patent: WO 9904690 A1 19990204
Application: WO 98US15165 19980724 (PCT/WO US9815165)
Priority Application: US 97900188 19970725
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AU CA JP AT BE CH CY DE DK ES FI FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 9223

FIVE RELATED DOCS, BENEATH

39/3/149 (Item 87 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00452737 **Image available**
METHOD AND APPARATUS FOR AUTOMATIC MUSCLE SEGMENTATION IN DIGITAL MAMMOGRAMS
PROCEDE ET APPAREIL DE SEGMENTATION AUTOMATIQUE DU TISSU MUSCULAIRE DANS LES CLICHES MAMMAIRES NUMERIQUES
Patent Applicant/Assignee:
R2 TECHNOLOGY INC,
Inventor(s):
KARSSEMEIJER Nico,
Patent and Priority Information (Country, Number, Date):
Patent: WO 9843201 A1 19981001
Application: WO 98US6207 19980327 (PCT/WO US9806207)
Priority Application: US 97825291 19970327
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AL AM AU AZ BA BB BG BR BY CA CN CU CZ EE GE GH GW HU ID IL IS JP KG KP KR KZ LC LK LR LT LV MD MG MK MN MX NO NZ PL RO RU SG SI SK SL TJ TM TR TT UA UZ VN YU GH GM KE LS MW SD SZ UG ZW AM AZ BY KG KZ MD RU TJ TM AT BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE BF BJ CF CG CI CM GA GN ML MR NE SN TD TG
Publication Language: English
Fulltext Word Count: 7427

FOUR RELATED DOCS, BENSAIH

39/3/155 (Item 93 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00388694 **Image available**
METHOD AND APPARATUS FOR TRAINING A NEURAL NETWORK TO DETECT AND CLASSIFY OBJECTS WITH UNCERTAIN TRAINING DATA
PROCEDE ET APPAREIL DE FORMATION D'UN RESEAU NEURONAL A LA DETECTION ET LA CLASSIFICATION D'OBJETS AVEC DES DONNEES DE FORMATION INCERTAINES
Patent Applicant/Assignee:
  SARNOFF CORPORATION,
Inventor(s):
  SPENCE Clay Douglas,
  PEARSON John Carr,
  SAJDA Paul,
Patent and Priority Information (Country, Number, Date):
  Patent: WO 9729437 A1 19970814
  Application: WO 97US2216 19970207 (PCT/WO US9702216)
  Priority Application: US 9611434 19960209
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
  CA JP KR MX AT BE CH DE DK ES FI FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 9976

THREE RELATED DOCS. BENEATH

39/3/164 (Item 102 from file: 349)
DIALOG(R)File 349:PCT FULLTEXT

00315897 **Image available**
NEURAL NETWORK FOR CELL IMAGE ANALYSIS FOR IDENTIFICATION OF ABNORMAL CELLS
RESEAU NEURONAL DESTINE A L'ANALYSE D'UNE IMAGE DE CELLULES AUX FINS D'IDENTIFICATION DE CELLULES ANORMALES
Patent Applicant/Assignee:
UROCOR INC,
Inventor(s):
VELTRI Robert W,
ASHENAYI Kaveh,
HU Ying,
O'DOWD Gerard J,
Patent and Priority Information (Country, Number, Date):
Patent: WO 9534050 A1 19951214
Application: WO 95US7005 19950601 (PCT/WO US9507005)
Priority Application: US 94253933 19940603
Designated States:
(Protection type is "patent" unless otherwise stated - for applications prior to 2004)
AU CA JP AT BE CH DE DK ES FR GB GR IE IT LU MC NL PT SE
Publication Language: English
Fulltext Word Count: 25312

TWO RELATED DOCS, BENEATH

```
Set     Items   Description
S1     4224037   IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT-
                ()(MAP OR MAPS OR MAPPED OR MAPPING)
S2     5271882   SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO-
                RIAL? OR XRAY? OR X()(RAY OR RAYS OR RAYED OR RAYING) OR RADI-
                OGRA?
S3     1573623   PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON()EMISS-
                ION? OR MAGNETIC?()RESONANC? OR MRI
S4     1063560   TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT)()SCAN? -
                OR CTSCAN?
S5     6881368   COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6      579887   DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO
                OR DATA OR CENTRAL)()PROCESS?
S7       54213   PROCESS?(2N)(MODULE? OR UNIT?)
S8       15892   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S9      691575   MACHINE?(2N)LEARN? OR MACHINE()VECTOR? OR NEURAL()NETWORK?
                OR ARTIFICIAL()(NEURAL? OR INTELLIGEN?) OR BACK()PROPAGAT? OR
                OPTIM?()(HYPERPLAN? OR HYPER()PLAN?) OR CYBERNET?
S10      71273   PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF-
                ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?)(2W)PROCESS?
S11     147054   IDENTIF?(3N)(MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR
                TRANSCOD? OR DATA(3N)(MODIF? OR CONVERT? OR CONVERSION? OR AL-
                TER? OR CHANGE? OR CHANGING)
S12      31322   TRANSFORM? ?(3N)(RADON OR HOUGH) OR PRECLASSIF? OR PRE()(P-
                ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13    3672601   TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG-
                HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14       1026   S1:S4 AND S5:S7 AND S8:S9 AND S10:S12 AND S13
S15        730   S14 AND PY<2000
S16        334   S15 AND S1:S4(5N)S5:S7
S17        152   S16 AND S1:S4(5N)S10:S12
S18        176   S16 AND S1:S4(5N)S8:S9
S19         90   S17 AND S18
S20         75   RD (unique items)
? show files
File   2:INSPEC 1969-2005/May W4
         (c) 2005 Institution of Electrical Engineers
File   6:NTIS 1964-2005/May W4
         (c) 2005 NTIS, Intl Cpyrght All Rights Res
File   8:Ei Compendex(R) 1970-2005/May W3
         (c) 2005 Elsevier Eng.  Info. Inc.
File  34:SciSearch(R) Cited Ref Sci 1990-2005/May W5
         (c) 2005 Inst for Sci Info
File  35:Dissertation Abs Online 1861-2005/May
         (c) 2005 ProQuest Info&Learning
File  62:SPIN(R) 1975-2005/Mar W3
         (c) 2005 American Institute of Physics
File  65:Inside Conferences 1993-2005/May W5
         (c) 2005 BLDSC all rts. reserv.
File  73:EMBASE 1974-2005/May W4
         (c) 2005 Elsevier Science B.V.
File  94:JICST-EPlus 1985-2005/Apr W2
         (c)2005 Japan Science and Tech Corp(JST)
File  95:TEME-Technology & Management 1989-2005/Apr W4
         (c) 2005 FIZ TECHNIK
File  99:Wilson Appl. Sci & Tech Abs 1983-2005/Apr
         (c) 2005 The HW Wilson Co.
File 111:TGG Natl.Newspaper Index(SM) 1979-2005/May 31
         (c) 2005 The Gale Group
File 144:Pascal 1973-2005/May W4
         (c) 2005 INIST/CNRS
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File 155:MEDLINE(R) 1951-2005/May W5
         (c) format only 2005 The Dialog Corp.
File 256:TecInfoSource 82-2005/Apr
         (c) 2005 Info.Sources Inc
File 434:SciSearch(R) Cited Ref Sci 1974-1989/Dec
         (c) 1998 Inst for Sci Info
?
```

20/3,K/9 (Item 9 from file: 2)
DIALOG(R)File 2:INSPEC

4868241 INSPEC Abstract Number: A9504-8760J-031, C9503-7330-050
Title: Automatic segmentation of liver structure in CT images **using a** neural network
Author(s): Tsai, D.-Y.
Author Affiliation: Gifu Nat. Coll. of Technol., Japan
Journal: IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences vol.E77-A, no.11 p.1892-5
Publication Date: Nov. 1994 Country of Publication: Japan
CODEN: IFESEX ISSN: 0916-8508
Language: English
Subfile: A C

Title: Automatic segmentation of liver structure in CT images **using a** neural network
Abstract: Describes a segmentation method of liver structure from abdominal CT **images** using a three-layered **neural network** (NN). Before the NN segmentation, **preprocessing** is employed to locally enhance the contrast of the region of interest. Postprocessing is also...

... the proposed method, the NN-determined boundaries are compared with those traced by two highly **trained** surgeons. The author's preliminary results show that the proposed method has potential utility in...
Descriptors: **computerised tomography** ; ...

... **image** segmentation...

...medical **image** processing
...Identifiers: abdominal CT **images** ; ...

...3-layered **neural network** ; ...

...medical diagnostic **imaging** ; ...

... **image preprocessing** ;
1994

20/3,K/23 (Item 7 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

04365106 E.I. No: EIP96033110480
Title: Determining and classifying the region of interest in ultrasonic images **of the breast using** neural networks
Author: Buller, Danuta; Buller, Andrzej; Innocent, Peter R.; Pawlak, Waldemar
Corporate Source: City Hospital, Wejherowo, Pol
Source: Artificial Intelligence in Medicine v 8 n 1 Feb 1996. p 53-66
Publication Year: 1996
CODEN: AIMEEW
Language: English

Title: Determining and classifying the region of interest in ultrasonic images **of the breast using** neural networks
Abstract: This paper describes how **ultrasonic images** of the female breast have been processed and neural nets used to aid the identification of malignant and benign areas in them. The **images** are windowed, filtered and **pre - processed** into suitable patterns for processing by a neural net. Two networks are **trained** and used: one for malignant cases and the other for benign cases. These are used to make predictions of regions of interest which are presented as circles overlaid on the **image** . The system has been prototyped and tested and experts agreed well with the classification and localization. The system is usually weak when the evidence on the **image** is considered weak by the expert. It is concluded that the system is promising and should be developed further by providing more **training** to the network. (Author abstract) 24 Refs.
Descriptors: ***Compute** r aided diagnosis; **Neural networks** ; **Ultrasonic imaging** ; Medical **imaging** ; **Image** analysis; Pattern recognition

20/3,K/25 (Item 9 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

04055613 E.I. No: EIP95012534210
Title: **Fourier-transformed** preprocessing **used in a noniteratively-** trained **perceptron pattern recognizer**
Author: Hu, Chia-Lun J.
Corporate Source: Southern Illinois Univ at Carbondale, Carbondale, IL, USA
Conference Title: Proceedings of the 1994 IEEE International Conference on Neural Networks. Part 5 (of 7)
Conference Location: Orlando, FL, USA Conference Date: 19940627-19940629
E.I. Conference No.: 42367
Source: IEEE International Conference on Neural Networks - Conference Proceedings 5 1994. IEEE, Piscataway, NJ, USA,94CH3429-8. p 3020-3023
Publication Year: 1994
CODEN: 001762
Language: English

Title: **Fourier-transformed** preprocessing **used in a noniteratively-** trained **perceptron pattern recognizer**
Abstract: When a **digitized image** is **preprocessed** by spatial quantizations in a polar-coordinate, the analog vectors representing the r and the theta quantizations can be treated separately in **neural network trainings** . If we apply a segmented Fourier transform (similar to FFT) to the theta vector and a segmented Hankel transform to the r vector in a noniterative perceptron **training** system, then not only the **learning** of the **training** patterns is very fast (e.g., 2 seconds for **learning** 4 **training** patterns), but also the recognition of an untrained pattern is very robust. Specially the recognition is very robust when the test pattern is rotated even though all the **training** patterns are not rotated in space. The high robustness of recognization is due to the special **preprocessing** scheme and the optimum noniterative **training** scheme we adopted in the design. This paper concentrates at the theoretical origin and the experimental results of the robustness of this novel perceptron **learning** system. An unedited **video** movie of the whole **training** /recognition experiment is recorded in real time for demonstration purpose. (Author abstract) 5 Refs.
Descriptors: ***Neura l networks** ; Pattern recognition; **Image** processing; Vectors; Fast Fourier transforms; **Learning** systems; Real time systems; Optimal systems; Pattern recognition systems; Robustness (control systems)
Identifiers: Fourier transformed **preprocessing** ; Noniteratively **trained** perceptron pattern recognizer; Spatial quantizations; Non conventional **training** ; Unsupervised **learning**

20/3,K/28 (Item 12 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

03678877 E.I. No: EIP93081044164
Title: Recognizing cancer cells from images **of stomach smears**
Author: Hong, Qin; He, Zhenya; Wu, Chengwu; Wang, Taijun
Corporate Source: Southeast Univ, Nanjing, China
Source: Zhongguo Shengwu Yixue Gongcheng Xuebao/Chinese Journal of Biomedical Engineering v 12 n 1 Mar 1993. p 56-60, 34
Publication Year: 1993
CODEN: ZSYXEI ISSN: 0258-8021
Language: Chinese

Title: Recognizing cancer cells from images **of stomach smears**
Abstract: This paper discussed the application of **digital image** processing and pattern recognition to the diagnosis of stomach smears. Under the supervision of pathologists, cell **images** are collected and divided into three classes: normal cells, cells between the normal and cancer, and cancer cells. At first, the cell **images** are **preprocessed** . The **images** are enhanced by histogram equalization and median filtering. Then by computing the threshold using the...

...the nucleus of a cell can be segmented. Six features were extracted from the cell **images** . A **neural network** approach for the classification was described. The utilized network is a multilayer perceptrons (MLP). The backpropagation **learning** is used for its **training** : The performance of the MLP was compared to traditional linear classifiers. It is shown that...
Descriptors: *Biomedical engineering; Gastroenterology; Oncology; Cytology; **Image** analysis; **Image** processing
Identifiers: Stomach cancer cell; Cancer cell **image** recognizing

20/3,K/31 **(Item 15 from** file: 8)
DIALOG(R)File 8:Ei Compendex(R)

03531561 E.I. Monthly No: EIM9212-064694
Title: Neural network **diagnosis of avascular necrosis from** magnetic resonance images .
Author: Manduca, A.; Christy, P.; Ehman, R.
Conference Title: Proceedings of the 13th Annual International Conference of the IEEE Engineering in Medicine and Biology Society
Conference Location: Orlando, FL, USA Conference Date: 19911031
E.I. Conference No.: 17015
Source: Proceedings of the Annual Conference on Engineering in Medicine and Biology v 13 pt 3. Publ by IEEE, IEEE Service Center, Piscataway, NJ, USA (IEEE cat n 91CH3068-4). p 1429-1431
Publication Year: 1991
CODEN: CEMBAD ISSN: 0589-1019 ISBN: 0-7803-0216-8
Language: English

Title: Neural network **diagnosis of avascular necrosis from** magnetic resonance images .
Abstract: **Artificial neural networks** has been used to diagnose avascular necrosis (AVN) of the femoral head from **magnetic resonance images** . Multilayer perceptron networks, **trained** with conjugate gradient optimization, which diagnose AVN from single sagittal **images** of the femoral head with 100% accuracy on the **training** data and 97% accuracy on test data has been developed. These networks use only the raw **image** as input (with minimal **preprocessing** to average the **images** down to 32 multiplied by 32 size and to scale the input data values) and **learn** to extract their own features for the diagnosis decision. Various experiments with these networks, whose results are considered to be very encouraging for the use of **neural networks** in diagnostic radiology, are described. 9 Refs.
...Descriptors: **Computer** Aided Diagnosis; **NEURAL NETWORKS** ; **MAGNETIC RESONANCE IMAGING** ; **IMAGE** PROCESSING...

... **Image** Analysis; **RADIOGRAPHY**
Identifiers: AVASCULAR NECROSIS DIAGNOSIS; **NEURAL NETWORK** DIAGNOSIS; MULTILAYER PERCEPTRON NETWORK; CONJUGATE GRADIENT OPTIMIZATION; DIAGNOSTIC RADIOLOGY

20/3,K/49 (Item 16 from file: 34)
DIALOG(R)File 34:SciSearch(R) Cited Ref Sci

02334321 Genuine Article#: KV204 No. References: 53
Title: ADVANCED MACHINE LEARNING **TECHNIQUES FOR** COMPUTER **VISION**
Author(s): MOSCATELLI S; KODRATOFF Y
Corporate Source: CNRS,BAT 490/F-91405 ORSAY//FRANCE/; UNIV PARIS 11,LRI/F-91405 ORSAY//FRANCE/
Journal: LECTURE NOTES IN ARTIFICIAL INTELLIGENCE, **1992** , V617, P161-197
ISSN: ****-****
Language: ENGLISH Document Type: ARTICLE (Abstract Available)

Title: ADVANCED MACHINE LEARNING **TECHNIQUES FOR** COMPUTER **VISION** , **1992**
Abstract: **Learning** is a critical research field for autonomous **computer** vision systems. It can bring solutions to the knowledge acquisition bottleneck of **image** understanding systems. Recent developments of **machine learning** for **computer** vision are reported in this paper. We describe several different approaches for **learning** at different levels of the **image** understanding process, including **learning** 2-D shape models, **learning** strategic knowledge for optimizing model matching, **learning** for adaptative target recognition systems, knowledge acquisition of constraint rules for labelling and automatic parameter...
...Research Fronts: FOR CMOS HIGH-PERFORMANCE CIRCUITS)
91-4728 002 (KNOWLEDGE ACQUISITION; DISCOVERY OF PROBLEM-SOLVING STRATEGIES; **LEARNING** PLAN SCHEMATA)
91-1259 001 (**HOUGH TRANSFORM** ; OBJECT RECOGNITION; **COMPUTER** VISION; RANGE **IMAGES** ; CURVE DETECTION)

20/3,K/55 (Item 2 from file: 35)
DIALOG(R)File 35:Dissertation Abs Online

01539663 ORDER NO: AAD97-11033
AN AUTOMATED SYSTEM FOR THE CLASSIFICATION OF MAMMOGRAMS (COMPUTER **AIDED DIAGNOSIS)**
Author: COOLEY, TIMOTHY RICHARD
Degree: PH.D.
Year: **1996**
Corporate Source/Institution: RUTGERS THE STATE UNIVERSITY OF NEW JERSEY - NEW BRUNSWICK (0190)
Source: VOLUME 57/11-B OF DISSERTATION ABSTRACTS INTERNATIONAL. PAGE 7073. 191 PAGES

AN AUTOMATED SYSTEM FOR THE CLASSIFICATION OF MAMMOGRAMS (COMPUTER **AIDED DIAGNOSIS)**
Year: **1996**

This dissertation describes a new approach to the automated processing of **mammograms** . Previous research centered on **Computer** Aided Diagnosis (CAD) which assists a radiologist in their interpretation of the **image** . Oftentimes these systems would only process manually specified regions of the **mammogram** . This system takes a **mammogram** as a whole and classifies it as normal (Category I) or abnormal (Categories II, III...
...of system could be used as a first screening tool for locations that have no **trained** radiologist. One such location is the mobile **mammography** vans which perform screening **mammography** at various places. It could also be of use in a "second opinion" role providing additional information to a **trained** radiologist.

The system is composed of three distinct modules: **Image** acquisition, Image pre-processing, and **Image** classification. To acquire the **digitized** **image** the **mammogram** is scanned with a flat-bed transparency scanner at a resolution of less than 65 μm. The **digitized** **mammogram** is then **pre - processed** by a five octave, multi-resolution wavelet transform. Features are extracted by the novel technique...

...Additional features are obtained by computing the invariant moments and the entropy of the original **image** . These features are then used to classify the **mammogram** by a modular feed-forward **neural** **network** which is **trained** using the ALOPEX optimization algorithm.

The system was **trained** on 49 **mammograms** , 28 normals and 21 abnormals, and tested on 10 **mammograms** , 6 normals and 4 abnormals. **Training** performance of greater than 93 percent was consistently achieved. By curtailing the **training** prior to the network becoming overtrained, validation performance of 100 percent was reached. Since **mammograms** are viewed as one of the most difficult **images** to process, these methods should also perform well with other **image** types.

20/3,K/70 (Item 8 from file: 144)
DIALOG(R)File 144:Pascal

12802423 PASCAL No.: 97-0015512
Application of neural network **-based multi-stage system for detection of microcalcification clusters in** mammogram images : Computer **-aided diagnosis I**
Image **processing : Newport Beach CA, 12-15 February 1996**
LURE F Y M; GABORSKI R S; PAWLICKI T F
LOEW Murray H, ed; HANSON Kenneth M, ed
Eastman Kodak Company, Rochester, NY 14650-2123, United States
International Society for Optical Engineering, Bellingham WA, United States.
Image processing. Conference (Newport Beach CA USA) 1996-02-12
Journal: SPIE proceedings series, **1996** , 2710 16-23
Language: English

Application of neural network **-based multi-stage system for detection of microcalcification clusters in** mammogram images : Computer **-aided diagnosis I**
Image **processing : Newport Beach CA, 12-15 February 1996**
1996

A multi-stage system with **image** processing and **artificial neural** techniques is developed for detection of microcalcification in **digital mammogram images** . The system consists of (1) **preprocessing** stage employing box-rim filtering and global thresholding to enhance object-to-background contrast ; (2...

... erosion, connected component analysis, and suspect region segmentation to select potential microcalcification candidates ; and (3) **neural network** -based pattern classification stage including feature map extraction, pattern recognition **neural network** processing, and decision-making **neural network** architecture for accurate determination of true and false positive microcalcification clusters. Microcalcification suspects are captured and stored in 32 x 32 **image** blocks, after the first two processing stages. A set of radially sampled pixel values is utilized as the feature map to **train** the neural nets in order to avoid lengthy **training** time as well as insufficient representation. The first pattern recognition network is **trained** to recognize true microcalcification and four categories of false positive regions whereas the second decision...

... identify true cluster at an accuracy of 93% with 2.9 false positive microcalcifications per **image** .

English Descriptors: Malignant tumor; Mammary gland; Woman; **Mammography** ; **Computer aid** ; Diagnostic aid; **Digital image** ; Microcalcification; Diagnosis; **Neural network** ; Multistage process; **Image** processing; **Image** analysis

French Descriptors: Tumeur maligne; Glande mammaire; Femme; **Mammographie** ; Assistance ordinateur; Aide diagnostic; **Image** numerique; Microcalcification; Diagnostic; Reseau neuronal; Procede etage; Traitement **image** ; Analyse **image**

Spanish Descriptors: Tumor maligno; Glandula mamaria; Mujer; Mastografia; Asistencia ordenador; Ayuda diagnostica; **Imagen** numerica; Microcalcificacion; Diagnostico; Red neuronal; Procedimiento

poliescalonado; Procesamiento **imagen** ; Analisis **imagen**
Broad Descriptors: Human; Mammary gland diseases; Biomedical engineering; Biomedical **data processing** ; Radiodiagnosis; Homme; Glande mammaire pathologie; Genie biomedical; Informatique biomedicale; Radiodiagnostic; Hombre; Glandula mamaria patologia; Ingenieria...

20/3,K/75 (Item 4 from file: 155)
DIALOG(R)File 155:MEDLINE(R)

10997191 PMID: 7777543
Neural - network **-based classification of cognitively normal, demented, Alzheimer disease and vascular dementia from single photon emission with computed** tomography image **data from brain.**
deFigueiredo R J; Shankle W R; Maccato A; Dick M B; Mundkur P; Mena I; Cotman C W
Department of Electrical and Computer Engineering, University of California, Irvine 92717, USA.
Proceedings of the National Academy of Sciences of the United States of America (UNITED STATES) Jun 6 **1995** , 92 (12) p5530-4, ISSN 0027-8424 Journal Code: 7505876
Contract/Grant No.: AG05142; AG; NIA
Publishing Model Print
Document type: Journal Article
Languages: ENGLISH
Main Citation Owner: NLM
Record type: MEDLINE; Completed

Neural - network **-based classification of cognitively normal, demented, Alzheimer disease and vascular dementia from single photon emission with computed** tomography image **data from brain.**
Jun 6 **1995** ,
Single photon emission with computed **tomography** (SPECT) hexamethylphenylethyleneamineoxime technetium-99 **images** were analyzed by an optimal interpolative **neural network** (OINN) algorithm to determine whether the network could discriminate among clinically diagnosed groups of elderly normal, Alzheimer disease (AD), and vascular dementia (VD) subjects. After initial **image preprocessing** and registration, **image** features were obtained that were representative of the mean regional tissue uptake. These features were extracted from a given **image** by averaging the intensities over various regions defined by suitable masks. After **training** , the network classified independent trials of patients whose clinical diagnoses conformed to published criteria for...

...80 and 86% for probable AD and probable/possible VD, respectively. These results suggest that **artificial neural network** methods offer potential in diagnoses from brain **images** and possibly in other areas of scientific research where complex patterns of data may have...
Descriptors: *Alzheimer Disease--radionuclide **imaging** --RI; *Brain --radionuclide **imaging** --RI; *Dementia, Vascular--radionuclide **imaging** --RI; * **Neural Networks (Computer**) ...; Middle Aged; Organotechnetium Compounds--diagnostic use--DU; Oximes--diagnostic use--DU; Technetium Tc 99m Exametazime; **Tomography** , Emission-Computed, Single-Photon

```
Set     Items   Description
S1     449547   IMAGE? OR IMAGING? OR GRAPHIC? OR VIDEO? OR BITMAP? OR BIT-
             ()(MAP OR MAPS OR MAPPED OR MAPPING)
S2      74183   SONOGRA? OR VISUAL? OR ULTRASOUND? OR ULTRASONIC? OR PICTO-
             RIAL? OR XRAY? OR X()(RAY OR RAYS OR RAYED OR RAYING) OR RADI-
             OGRA?
S3      34955   PHOTOGRAPH? OR PET(2N)SCAN? OR PETSCAN? OR POSITRON()EMISS-
             ION? OR MAGNETIC?()RESONANC? OR MRI
S4       1290   TOMOGRAPH? OR MAMMOGRA? OR CATSCAN? OR (CAT OR CT)()SCAN? -
             OR CTSCAN?
S5    1006260   COMPUTER? OR DIGITAL? OR DIGITIZ? OR DIGITIS? OR BINARY?
S6     118467   DATAPROCESS? OR MICROPROCESS? OR CENTRALPROCESS? OR (MICRO
             OR DATA OR CENTRAL)()PROCESS?
S7      11818   PROCESS?(2N)(MODULE? OR UNIT?)
S8        252   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S9      17238   MACHINE?(2N)LEARN? OR MACHINE()VECTOR? OR NEURAL()NETWORK?
             OR ARTIFICIAL()(NEURAL? OR INTELLIGEN?) OR BACK()PROPAGAT? OR
             OPTIM?()(HYPERPLAN? OR HYPER()PLAN?) OR CYBERNET?
S10      4290   PREPROCESS? OR PREANALY? OR PREEXAMIN? OR PREPARS? OR (BEF-
             ORE? OR PRIOR? OR PRELIMIN? OR PREPARAT?)(2W)PROCESS?
S11     26089   IDENTIF?(3N)(MISSING? OR ERROR? OR ERRONEOUS? OR FLAW?) OR
             TRANSCOD? OR DATA(3N)(MODIF? OR CONVERT? OR CONVERSION? OR AL-
             TER? OR CHANGE? OR CHANGING)
S12       581   TRANSFORM? ?(3N)(RADON OR HOUGH) OR PRECLASSIF? OR PRE()(P-
             ROCESS? OR ANALY? OR EXAMIN? OR PARS? OR CLASSIF?)
S13    343198   TRAIN? OR LEARN? OR EDUCAT? OR INSTRUCT? OR TEACH? OR TAUG-
             HT? OR DIDACT? OR SELFTEACH? OR AUTODIDACT?
S14       448   S1:S4 AND S5:S7 AND S8:S9 AND S10:S12 AND S13
S15       394   S14 AND PY<2000
S16       364   RD (unique items)
S17       147   S16 AND S1:S4(5N)S5:S7
S18        32   S17 AND (PREPROCESS? OR PRE()PROCESS?)
? show files
File 275:Gale Group Computer DB(TM) 1983-2005/Jun 01
         (c) 2005 The Gale Group
File 647:CMP  Computer Fulltext 1988-2005/May W3
         (c) 2005 CMP Media, LLC
File 674:Computer News Fulltext 1989-2005/May W4
         (c) 2005 IDG Communications
?
```

18/3,K/14 (Item 14 from file: 275)
DIALOG(R)File 275:Gale Group Computer DB(TM)

01553332 SUPPLIER NUMBER: 13377714 (USE FORMAT 7 OR 9 FOR FULL TEXT)
Is neural computing the key to artificial intelligence **? (includes related articles on an explaination of neural computing, neural net chip speeds, neural computing challenging the status quo,** digital **signal processing and neural nets in medical research, and using neural nets in manufacturing loud speakers)**
Donlin, Mike; Child, Jeffrey
Computer Design, v31, n10, p87(14)
Oct, 1992
ISSN: 0010-4566 LANGUAGE: ENGLISH RECORD TYPE: FULLTEXT; ABSTRACT
WORD COUNT: 8391 LINE COUNT: 00699

Is neural computing the key to artificial intelligence **? (includes related articles on an explaination of neural computing, neural net chip speeds, neural computing challenging the status quo,** digital **signal processing and neural nets in medical research, and using neural nets in manufacturing loud...**

ABSTRACT: Advances in **neural network** technology has created increased interest in the thinking power of **computers** . In particular, there has been a renewed interest in neural computing in connection with **digital** signal processing, pattern recognition and forecasting. Certain common characteristics are shared by all **neural networks** . In the first place, they use some form of **learning** model to create their own representation of reality. Secondly, they use artificial neurons that are connected to at least one other neuron. Detailed is a history and explanation of **neural networking** . Areas discussed include **learning** by example, fuzzy logic, fast- **learning** chips, software-only **neural network** -specific products, the financial uses of neural computing and the impact of **neural networks** .

TEXT:

When people speculate about whether **computers** can **learn** to think, evil robots, such as Nomad running amok on the Starship Enterprise, often enter...

...Captain Kirk talks the sinister Nomad into blowing itself up, but the notion of a **computer** that can control human destiny makes many folks nervous. **Computer** professionals scoff at such silliness, even while acknowledging that advances in hardware and software have given **computers** the ability to emulate some human traits.

... room and could rip through mathematical calculations at a blistering 13 operations a second.

Presently, **computer** technology resides somewhere between ENIAC and Nomad, but advances in **artificial intelligence** , and particularly in **neural networks** , have caused a surge of interest in the thinking power of **computers** .

Nothing new about **neural networks**

The concept of **neural networks** has been around in some form since World War II, but it's only in the last six or seven years that working products have been developed that attempt to " **learn** " about and predict reality. In their infancy, **neural networks** and neural computing were the work of theorists who observed similarities in the way that **computers** and humans think. In both cases, a large amount of information is manipulated by breaking it into small particles--using gates in **computers**

and neurons in humans. Gates handle data by fluctuating between an "on" and "off' state...

...if the neurons were connected but not firing. Because of these similarities between human and **computer** thought, researchers have begun to explore ways to embody the structures of human intelligence in...
...100 billion neurons, each connected to 10,000 others by synapses. Building such a complex **computer** is a ridiculous idea, even with the staggering advances made in **computer** technology in the last twenty years.

Also, **neural networks** were dealt a blow in 1969 when Marvin Minski and Seymour Pappert wrote a book called Perceptrons, which postulated that **neural network** research was a waste of time. Minski, one of the rounding fathers of the **artificial intelligence** movement, refused to believe that software could simulate the behavior of human neurons. Minski's vision of **artificial intelligence** (M)was far more comprehensive than just **neural network** technology, and he scoffed at those who wanted to reduce his broad theories to a...

...of equations that could solve only simple problems. Many experts blame this book for derailing **neural network** research and encouraging the expert-system theories favored by the authors.

Expert systems, in turn...

...Although there are some areas where encoding the skills of an expert and programming a **computer** to carry them out seem feasible, for most complex tasks the intuition of an expert...

...expert makes decisions," says Steve Bissett, senior vice-president at Synaptics (San Jose, CA), a **neural network** IC firm. "The problem is that most experts can't tell you all the rules...

...difficult to codify. Even if you could write out enough knowledge to program into a **computer** , the amount of data would be so large that it would be prohibitively expensive to...

...emulate the neural connection model of the brain, both in hardware and in software, all **neural networks** share certain common characteristics: they use artificial neurons that are connected to at least one other neuron, and they create their own representations of reality based on some form of **learning** model.

I **Learning** by example

Fundamentally, all **neural networks learn** by association. For example, a **neural network** can **learn** to identify an apple by associating the inputs "round," "red" and "fruit" with the output "apple." The neurons in a **neural network** are usually organized in three layers: input, hidden and output. Sometimes more than one hidden layer is used for complex analysis.

There are many ways that **neural networks** can **learn** , but the most common way is through example and repetition, also called **back - propagation** . Each time an input is given to the network ("round," "red" or "fruit" from our...

...data, it will begin to zero in on the right answer. When it's fully **trained** , it can deliver an answer that's more or less accurate, depending on the complexity...

...this ability to gauge the importance of data that separates neural computing from a purely **digital** computational process. Although the synapses and weights can be made up of analog circuitry, **digital** components or software, the weighting procedure makes neural computing

appear to have an analog nature...

...as pattern recognition or financial forecasting.

"There's a key difference between neural computing and **digital** computing," Synaptics' Bissett points out. "Traditional **digital** computing is like the left-brain or logical thinking that we do. The **computer** receives a set of rules or programs, then takes input and produces output based on...Neural computing is more like right-brain thinking, which is intuitive. If you wanted a **computer** to read handwriting, you could try to write rules that would make it recognize an...

...previous knowledge to try and categorize it. An important distinction, then, is to try and **teach** by example rather than programming by rules."

The correlation of **neural networks** to the way our brains work is what makes them suited to applications that need experiential **learning**, but is neural computing really thinking? In a word, no. **Neural networks** are patterned after the architecture of the brain, but in reality their ability to think...

...a common housefly. As a matter of fact, some experts scoff at the notion that **neural networks** are related to human thought at all, other than in a purely analogous way.

"It...

...has nothing to do with building brains ," says Casimir Klimasauskas, president of NeuralWare (Pittsburgh, PA). " **Neural networks** are a collection of mathematical techniques that let you fit formulas to data, curves to data, and group types of data together. **Neural networks** could have been invented by statisticians, physicists or mathematicians, but the people who invented them were cognitive psychologists and neurobiologists, and so we ended up with the term **neural networks** . They have nothing to do with brains. I've found that if you try to explain **neural networks** from a human-thought perspective, people keep trying to fit them into a brain model...

...Enter fuzzy logic

In spite of such caveats, most people will probably continue to associate **neural networks** with human thought, particularly because much of the **learning** process in a **neural network** takes place in hidden layers or neurons, a processing paradigm similar to human thought. Some...

...functions by using fuzzy logic techniques to better understand, or even work in conjunction with, **neural networks** . Fujitsu (Kawasaki, Japan) is working on a system, for example, that creates a fuzzy rule...

...questionnaires that have been filled out by experts. These fuzzy systems are converted into a **neural network** , which **learns** about the task and refines its knowledge. Once the **neural network** has achieved an acceptable degree of accuracy, it's translated back into a fuzzy system...

...analyzed. According to Fujitsu researchers, this model reveals the hidden variables that develop in a **neural network** . By keeping the fuzzy rule sets and the **neural networks** as separate systems, the Fujitsu scientists believe they can **learn** more about how each system works.

But not everyone involved in combined fuzzy/neural computing...

...the disciplines separate. There's considerable activity in the AI community aimed at combining the **neural network** 's ability to create relationships with fuzzy logic's capability to produce input and output information that spans a range of behavior. One such approach builds fuzzy operations into the **learning** techniques used by a fuzzy/neural

controller. The resulting **neural network learns** to emulate a fuzzy controller, but with rules that can be altered by neural **learning** techniques.

In spite of the promise that the combination of fuzzy logic and **neural networks** holds, most of the work in this area is at the theoretical stage, although some practical applications have been demonstrated in medical **imaging** and flight simulation. To many theorists, however, the marriage of these two "smart" technologies seems inevitable.

Theories aside, most of the tangible products using either fuzzy logic or **neural networks** have come from research that treats each of these disciplines as separate entities. In the field of **neural networks** , this means three categories of products: **neural network** ICs, whose architectures are specifically designed for neural computing; **neural network** software, which uses standard **microprocessors** and **digital** signal processors to emulate **neural network** behavior; and **neural network** systems, which are turnkey **neural network computers** .

The first commercially available **neural networkspecific** chip was the 80170NX electrically **trainable** analog **neural** network (ETANN) device from Intel (Santa Clara, CA). Introduced in 1989, the chip is a 64 ...

...64 synapse arrays.

Intel has also released a development system so that you can simulate, **train** and operate a high-speed **neural network** . Dubbed the Intel **Neural Network Training** System (iNNTS), the package provides two 80170NX devices, two **learning** simulation software programs, diagnostic software, a programmer interface, an adapter that can run on PC/AT-compatible **computers** , programming specifications, and full documentation. The iNNTS contains two **learning** simulation software programs, iBrainmaker and DynaMind. The iBrainmaker program, developed by California Scientific Software (Grass Valley, CA), lets you simulate the network **learning** process through **back - propagation** techniques. In **back propagation** , you present the network model with a data set representing the application problem. Through simulation, iBrainmaker then **trains** the network to produce a desired response to specific inputs by assigning weights to each of the chip's analog storage elements. Once the network has been **trained** to solve the application problem, the weights are downloaded or programmed into the ETANN device.

The DynaMind simulation software, developed by NeuroDynamX (South Pasadena, CA), lets you simulate **back - propagation learning** , but also performs chip-in-loop **learning** . This technique optimizes the performance of the network by replacing the software simulation of the chip's performance characteristics and specifications with an actual device. The **neural network** can then " **learn** around" any minor processing variations occurring in individual ETANN chips.

Both iBrainmaker and DynaMind can also be used independently of the Intel development system to create **neural network** applications.

I Fastest- **learning** chip

A more recent **neural network** IC is the RN-200, a 256-synapse (16 synapses x 16 neurons) device that Ricoh (Tokyo, Japan) claims is the world's fastest- **learning** chip of its kind. The device boasts a front-end process of three billion connections per second and a **learning** speed of 1.5 billion connection updates per second (CUPs) when running at 12 MHz. In Tokyo, Ricoh demonstrated a desktop neural **computer** system that requires no software. Based on the first-generation RN-100 chip (a one...

...says will increase when the system incorporates the new RN-200.

One of the first **neural network** ASICS comes from Neural Semiconductor (Carlsbad, CA). Its CNU3232 has 32 inputs, 1,024 synaptic

weights and 32 nodes supporting its activation functions. The one-byte **digital** inputs and outputs and the weight-storage SRAM are all accessed through an 8-bit...
...O bus. Unlike the Intel chip, which uses analog elements, the CNU3232 is a purely **digital** device that's targeted at embedded system applications.
"We refer to ourselves as a neural...

...company," says Robert Bagby, president of Neural Semiconductor, "because we expect our customers to build **neural network** ICs of various sizes, topologies, precisions, and activation functions using our basic architecture. **Neural networks** are really multiple layers of nonlinear matrix multipliers. We build discrete circuitry for each and...

...have fully parallel neurons and fully parallel synapses or weights. Because our architecture is purely **digital** , designs based on it can be manufactured with standard processes for low-cost, high-volume "implementations."
The first **neural network** IC to find its way into a commercially available product comes from Synaptics. The chip, designed for optical character recognition (OCR), hosts an analog sensing array, two **neural networks** and a **digital** controller on a single device. The chip is at the heart of a check reader...

...says Synaptics' Bisset. "For most applications using a TV camera, that rate was just 30 **images** per second. By putting the sensor on the same chip with the classification circuitry, we...

...the same task thousands of times per second."
Other solutions
Not all hardware solutions for **neural network** applications are based on neural-specific silicon. There are systems that use standard **digital** components for neural computing, as well as for non-neural applications such as Fourier or...

...each with its own 4 kbytes of on-chip SRAM. A PN resembles a simple **digital** signal processor (DSP), and can be programmed for a variety of applications. At 25 MHz...

...billion multiply-adds per second. The chip falls somewhere between PC-based software solutions for **neural network** applications and silicon that's targeted at those applications.
"Given the performance of today's ?cs and workstations, you can emulate a lot of **neural network** applications in software alone," says Dan Hammerstrom, founder and chief technical officer at Adaptive Solutions ...

...chip. That's where flexibility pays off." I Software-only solutions The remaining category of **neural network** -specific products is software-only solutions, which emulate **neural networks** on workstations, Pcs and mainframes. These programs use either standard **microprocessors** or DSP chips to perform **neural networking** tasks, and are available from dozens of companies. The applications are as diverse as the...

...are being used for pattern recognition, financial analysis and defense-related projects.
In essence, most **neural network** tasks are based on some form of pattern recognition. Sometimes the sought-after pattern is a **visual** one--for example, a system that sorts good fruit from bad on a conveyor belt. In this application, the network must be **trained** to look for a vague trait such as "quality." "The customer who wanted to grade fruit had

to **train** the network to recognize color patterns that distinguished good apples from bad," says Ted Crooks, director of customer services at HNC (San Diego, CA), a **neural network** software vendor. "By repeatedly presenting data to the network, he **trained** it to discern the important relationships that define good quality--for example, 'this is premium...

...just gave examples of what characteristics are needed to place a piece of fruit there."

Visual pattern recognition is also being applied to medical research. Some hospitals are using a **neural network** to sift through hundreds of slides to detect anomalies in blood cells or tissue samples. Early results from these applications show that **neural networks** achieve a surprising level of accuracy when they're compared to a human performing the same task. As with most applications where a **computer** equals or bests a human being at a task, fatigue is the deciding factor. Although...human fatigue can cancel out some of that expertise, and the capabilities of human versus **neural network** begin to equalize.

In addition to recognizing flaws in cell structure, some physicians are using **neural networks** to help them with diagnosis and prognosis. "One of our customers is a neurosurgeon who's using **neural networks** to predict potential IQ loss after brain surgery," says Jim Blodgett, director of marketing for...

...statistics are fine. But in the middle of the curve there can be large variations. **Neural networks** can use factors such as the severity of an injury or a patient's medical history to make predictions of an operation's outcome ." I Financial uses While **neural network** research in medicine makes for dramatic reading, there are other applications, particularly in the realm of finance, that might have even greater ramifications. Banks are relying on **neural networks** to do everything from predicting loan eligibility to spotting credit-card fraud. In the case of loan eligibility, the network is **taught** to examine the factors that would make a good loan applicant, based on profiles of...

...the data, such as income, time on the job, credit history, and so on, but **neural networks** look for unusual patterns or relationships which might escape a human, particularly a human who...

...a gourmet meal in a 24-hour period.

The common denominator in these applications is **training** the network to look for subtle shifts in patterus which are crucial to making a ...

...which stocks produce returns better or worse than expected."

The lure of networks

Obviously, developing **neural networks** that can accurately predict what was once thought to be unpredictable is a tantalizing prospect...

...of these stories sound like hype, especially when they're playing to an audience of **computer** professionals who've seen their share of flash-inthe-pan technologies over the years. Still, there is an element of mystery to many **neural network** applications.

"We think there's a lot more going on, particularly in financial circles, than...

...the only area where more mystery prevails than on Wall Street is in defense-related **neural network** applications. Most of the people involved in such projects are understandably reluctant to discuss the details of their activities, but it's clear that **neural networks** are being used for such things as missile guidance systems.

"We became interested in **neural networks** about six or seven years ago, when other **artificial intelligence** solutions proved to be too slow for our applications," says Dr. David Andes, research fellow...

...all, the purpose of the device is to deliver explosives, not electronics. We got into **neural networks** because biological brains do the type of computing that we need, and they do it...

...stem that can hit a target without needing human intervention.

Naturally, for these applications a **neural network** must be **trained** to recognize a target in the confusion of battle, something that heat-seeking devices find problematic. But trying to give a **neural network** enough data to find targets in rapidly changing battle situations is a daunting task.

" **Neural networks** are notorious for picking up on things that you don't want them to," Andes cautions. "We heard about one application where a **neural network** was picking out the enemy from a **visual** field with perfect accuracy. Naturally, everyone got suspicious and investigated more closely. It turned out...

...no hum, good guy. They took away the hum and the network was lost." I **Neural network** 's impact When the breadth of **neural networking** applications is ...to separate fact from fiction is difficult, particularly when those who are really successful with **neural networks** are reluctant to divulge too many details. And so the questions remain--can you use a **neural network** in your job, and how will **neural networks** ultimately affect your life?

As far as jobs are concerned, **neural networks** are best suited to analytical tasks that prove too complex or firing for humans to perform accurately. And certainly because **neural networks** are based on **computer** technology, they will affect the electronics industry if they're widely embraced.

Technological applications of **neural networks** are, in fact, starting to see the light of day. Last February, for example, Intel announced a breakthrough in **neural networking** , the capability not only to identify patterns but also to read out their locations. The...
...at 6 o'clock--like a pilot reporting an enemy's position in the sky.

Neural networks could also conceivably guide placement and routing algorithms for chip and printed circuit board design...

...your spine, you're not alone. Although it's far too soon to predict whether **neural networks** are another headline-grabbing M story or the beginning of a **computer** revolution, one thing is clear. The **photographs** that accompany this article are taken from real applications. Somewhere a **computer** might be grading the apples that you eat. It may be deciding whether to give...

...a job interview. And because most of you reading this article are familiar with what **computers** can and can't do, you're either smiling fight now--or feeling a little queasy.

In these examples of pattern recognition from HNC, the **neural network** 's ability to **learn** by association shows the technology to be promising for everything from fruit grading to target recognition for weapons systems.

The apple grading system captures **images** and feeds them to a **neural network** , which eventually **learns** how to determine which characteristics affect an apple's quality. Once the network is **trained** , the system can classify an apple by comparing its traits to the network's **learned** base.

"The tank recognition system," says Ted Crooks, director of customer

services at HNC, "was actually an experiment to prove that **neural networks** could be used in defense systems. Critics of **neural networks** cited an application where a **trained** neural system picked out tanks flawlessly until it was discovered that all pictures of tanks...

...As soon as those clues were taken away, the network failed. We proved that a **neural network** could indeed be **trained** to differentiate a tank's shape from other objects, and that experiment led to a real application,"

In this picture, a filtered **image** of two tanks is outlined so that the network can **learn** to differentiate them from other objects.

For this Special Report on Future Computing, **Computer** Design interviewed Carver Mead, an expert on the subject of neural computing. Professor Mead is the Gordon and Betty Moore Professor of **Computer** Science at the California Institute of Technology, where he has **taught** for 20 years. He's also a co-founder and chairman of Synaptics, a company that develops **neural network** technology Mead has pioneered in many areas of electronics, from the invention of the MESFET to silicon compilers and, recently, VLSI analog neural systems.

Computer Design: After many years of use in academic circles, neural computing now appears poised to...

...Mead: Your question reminds me of how people used to talk about parallel architectures in **computers** years ago. People said: "We do things in a topdown way." And I'd ask...

...the beginning, so you have to evolve your understanding along with the application.

In the **neural network** business that top-down approach has translated into some rather abortive attempts to make general-purpose **neural network** chips. Those chips haven't worked well because no one knows what architecture is right...generalize from.

CD: How will future advances in VLSI process technology influence the capabilities of **neural network** chips? Do you see any potential roadblocks? Mead: Silicon process technology is very relevant to neural computing. A lot of people have tried to invent brand-new technologies to do **neural networks** . But it's important to remember that we are riding on the coattails of a...

...immediately applicable to this adaptive analog approach. That's not true of other approaches to **neural networks** .

Transistors as analog devices

CD: As I understand it, your neural net chip uses the transistors in **digital** semiconductors in an analog way.

Mead: Yes. Transistors are analog devices. Let them be what they are. **Digital** IC designers have had to work so hard to turn them into 1s and Os ...

...The inputs and the intermediate signals are inherently analog signalsthey're typically faked out by **binary** numbers right now in a **computer** simulation, but that's not the effective way to use them. The effective way is for them to evolve in real time as analog signals. **Digital computers** not only turn signals into **digital** values, but they also use discrete time. Those discrete time stamps actually destroy information by aliasing. And because a **neural network** is nonlinear, there's no theory that tells you how much information you've lost...

...way.

Fortunately, the transistors in semiconductors never did know that they were supposed to be **digital** . They're inherently analog by nature.

That means you can use them that way, and...

...s why the adaptive part is so important. Because, not only do you let the **neural networks learn** from their environment, but they also adapt to changes in the environment. And one of...

...in this path. In fact, we're seeing that as the technologies are evolving for **digital** use, they're actually evolving capabilities that we use in an analog way to make them even more effective.

The analog- **digital** continuum CD: It seems clear that neural computing is not destined to replace traditional logical...

...of a pixel or the value of a waveform, to take two examples. And the **digital** world deals with discrete symbols: the letters of the alphabet, for example. At some point...

...the classifier was a relay. Then you had a contact closure and that was your **digital** output. It turned on a light or a heater element in a furnace or something...

...antialias filtering and a multiplexer on the analog side. Then there's an analog-to- **digital** converter, which you could think of as the most brain-dead classifier you can imagine. Because all it does is take analog values and convert them into **binary** numbers which represent voltage changes. The **computer** is expected to manipulate these values as if they were numbers and eventually simulate a...
...example, you'd want to classify the data into phonemes. Our 1-1000 chip classifies **images** directly into character codes. A character code is a lot more meaningful to the **computer** than the analog values of the pixels. **Computers** are the way to handle discrete symbols, but they ought to be appropriate discrete symbols...

...You use an analog classifier to decide what the best classification is. That has a **digital** output which goes into a **digital** system.

Many of the **neural network** chips available today are aimed at that classifier job. But they're leaving out all...

...end of the spectrum is done by adaptive analog technology and the stuff on the **digital** end is done by **digital computers** (as it is today). And the classification in the middle, between the two, is done...

...level. And that's just plain good engineering. So we're not talking about replacing **digital computers** . It's just a matter of recognizing which technology is most natural for each situation.

CD: Today a lot of **neural networks** are simulated in software on large, powerful **computers** .

Mead: Right. It takes too much **digital** computing for the size of the problem. That limits the applications to the very few, where time isn't critical and you've got the processing power of a Cray **computer** around. It's only by getting this balance in the technologies that we're going...

...or 10 years from now?

Mead: If you look at the continuum between analog and **digital** , we've gone all the way from 90 percent of the system being on the analog side to 90 percent on the **digital** side. We're headed back toward a balance of about half and half. Over the...

...in general are headed.

Any biomedical technician can probably do a better job than a **computer** of **visually** identifying reactions in blood cells. But when

researchers at the University of California (Davis, CA...

...day, and do so accurately and consistently, they moved to an automated approach that combines **digital** signal processing (DSP)with a **neural network** simulated in software.

At first glance, the application seemed like a simple **image** classification problem. Bloodcell **images** are captured using a high-resolution CCD (chargecoupled device) camera attached to a microscope. Each **image** is about a millimeter and a half in diameter. That area contains about 100,000...

...may or may not occur. The photos show four degrees of reaction into which the **neural network** classifies **images** .

There's added complexity, however, because no two reactions are exactly the same. The network also has to account for rotated views of the exact same **image** . For example, if a human were looking at the **image** and felt he or she could better identify the reaction from another angle, the **image** could simply be rotated. For the **computer** this would be very complicated. You'd have to show the network how the **image** looked rotated 5 degrees, and that means the network would have to analyze 72 different versions of the same **image** . In **back - propagation** neural nets, the difficulty of **training** increases proportionally to the number of **training** examples raised to the third power.

Preprocessing needed

"In **neural networks** , the more work you can do before you hand off the project to the neural...

...are," explains Wasyl Malyj, associate development engineer at uc Davis. With this in mind a **preprocessing** step was included to extract from the blood-cell **image** only its most critical data.

To accomplish this, a two-dimensional Fast Fourier Transform (FFT)is performed on the **image** 's pixel **data** , **converting** it into the frequency domain. This produces a compact feature vector. Sampling algorithms are applied to these vectors to extract useful information. The goal of the **preprocessing** is to take a very complex **image** with upwards of 512 x 512 (or over 1/4-million) pixels and extract from that a few hundred bytes of data. "The **preprocessing** reduced the amount of stuff that the neural net didn't need to **learn** , simplifying its structure, its **training** , and making it possible to implement the neural net with today's technology," says Malyj.

After the **image** is compressed into a complex feature vector, the vector is fed into the neural net...

...information through the net lets it adjust its connection strengths, and in this way it " **learns** " to associate particular spectral patterns with particular reactions.

Because of the **preprocessing** , the input stage of the neural net is typically 128 neurons. To implement the network, the uc Davis researchers developed in software a custom-written **back - propagation** simulator capable of building nets with three or four layers. The code was written to run on a 486 working in conjunction with a Motorola 96002 floating-point **digital** signal processor (DSP).

The input layer typically has 128 neurons. The hidden, or middle, layers...

...covering the specimen, lack of blood or reagent in the reaction well, and proper focus.

Training the net According to Malyj, it took only about six hours to **train** the neural net. The DsP hardware helped boost its speed. A **training** set of about 800 **images** was shown to the neural net, along with the classification under which each **image** belongs. Once the neural net was **trained** , technicians began to feed it **images** that it had never seen

before for classification.
The network can be adjusted for various...

...as good as a human. But if we tell the net to classify only those **images** about which it's 'confident,' and to flag the others for us to take a look at, then it classifies about 85 percent of the **images** at better than 99 percent accuracy."
Researchers can then take the remaining 15 percent of the **images** and, after they've been scored by a human, use them to retrain the network ...

...applications that are suited for neura computing are tasks at which humans are better. But **computers** have an advantage over humans. They don't get tired or bored--even after several...
...repetitious work. With this in mind, engineers at CTS (Matamoros, Mexico) made use of a **neural network** in their loudspeaker manufacturing process.
At its plant, CTS manufactures several million loudspeakers per year. To ensure the quality of the units, a final inspection was performed by a **trained** operator, skilled at identifying audio defects.
This method had some disadvantages. An operator was required...

...that point that Rick Bono, a design engineer at CTS, decided to try using a **neural network** to classify the resuits of production testing. A **back - propagation** neural net was established, consisting of 10 input nodes, 18 hiddenlayer nodes and 4 output...

...four possible outputs identify good speakers and three classes of defective u n its.
To **train** the neural net, CTS ran over 200 units, both good and bad, through the process...

...classifying them into one of the four output classes. This required about 20 minutes of **computer** time on a 25-MHz 486. Once the network was **trained** , Bono integrated it into the test software using the NeuroShell run-time code generator from...
...now considering developing a second-generation system which would incorporate new cases as it works, **train** invisibly and then implement the new network. This would require a hardware-based implementation of **back - propagation** , says Bono.
Other upgrades might include adding more output nodes to the neural net. "We...

...seen different cases pop up--different defect cases that weren't included in the original **training** ," says Bono. "They have distinct patterns, and the net can be **trained** to recognize them."
DEVELOPMENT TOOL VENDORS
List courtesy of Martin Middlewood and Tom Schwartz.
Adaptive Solutions
CNAPS: Development en
-vironment includes CNAPS
assembler and library of
neural network algorithms.
(503) 690-1236
AI Ware
N-NET EX: User and pro
-gram interfaces, functional
link net architecture, asso
-ciative recall. Supervised and
unsupervised **learning** .

(216).421-2380
AND America
HNet: Neural-based de
-velopment system using dig
-ital holography...

...Transputer- and Pc/Win
-dows-based versions.
(416) 569-0897 (Canada)
Applied Cognetics
WinBrain: Develops **back**
- **propagation** networks. In
-corporates multiple trans
-formational models.
(212) 969-8769
California Scientific
Software
Brainmaker: Basic...

...neurons, up to six hidden
layers. Tutorial and eight
sample networks. Imports
Excel, Lotus, dbase, **binary** ,
and ASIC files. Print/edit
neuron matrices.
(800) 2848112
EPIC Systems Group
Neuralyst: Integrates
neural networks with Excel
spreadsheets. Includes
macro library for investment
analysis.
HNC
ExploreNet 3000: Win
-dows-based application
software program for devel
-oping and implementing
neural network solutions
without programming.
Database mining program
available also.
(619) 546-8877 / Circle 372
Hyperlogic
Owl **Neural Network** Li
-brary: Twenty-four functions
for accessing networks sup
-plied as C library. Twenty
types of **neural networks** .
(619) 746-2765
ImageSoft
ExperNet: Object-ori
-ented tool for creating Win
-dows-based neural net
-works and knowledge
applications.
(800) 245-8840
Inductive Solutions
NNetSheet: Supports
nine algorithms for super
-vised and unsupervised

training . **Train** network can
be potted to a spreadsheet.
(212) 945-0630
Mathworks
Neural **Network** Toolbox:
Includes **learning** rules,
transfer functions and **train**
-ing and design procedures
for implementing **neural**
networks .
(508) 653-1415
Martingale Research
SYSPRO: FORTRAN-based
neura network simulation
and prototyping tool.
(214) 4224570
Neural **Computer**
Sciences
NeuralDesk: Supports
many algorithms. Manual
and automatic **training** of
neural **networks** .
44-703-667775 (UK)
Neural Systems
Genesis: Development
environment for interfacing
neural **networks** to applica
-tion software.
(604) 263-3667 (Canada)
NeuralWare
NeuralWorks: Neural net
-work chip development,
open architecture, 8-k **back**
- **propagation** , makes net
-work types from libraries
and creates diagnostic tools.
(412) 787-8222
Neurix
MacBrain: Flexible neural
connections, activation
rules, 3-D graphs, interactive
modeling, **visual** macro lan
-guage.
(617) 426-5096 l Circle 381
NeuroDynamX
DynaMind: **Train** net
-works on Intel's 80170NX
ETANN and Intel multichip
board. Can read and store
network **trained** in emula
-tion mode and download
weights to chip.
(800) 747-3531
NeuroSym
Neural CASE...

...BPN. CPN, RN, and SOM.
(713) 523-5777
Peak Software
Autonet: Constructs net

-works from **training** data
sets consisting of input vari
-ables and expected results.
Networks may also be cre
-ated from command line.
(612) 854-0228
SAIC **Artificial** **Neural**
Systems
Delta ANSpec: Language
for defining and implement
-ing parallel distributed pro
-cessing systems.
(619) 546-6005
Software Bytes
ET 2.0: Simulates text,
graphics and Windows.
Back-error propagation
neural **networks** with Bor
-land C/C++ source code, ET
Graphics and Windows slide
neural **networks** on equiva
-lent VGA screens
(800) 5214119
Software Frontiers
Neural **Network** Toolkit:
Development software for
neural **network** applications.
C source code included.
(800) 475-9082
Talon Development
Brain: Lotus 1-2-3...
...A 5-billion
-connection-per-second
neurocomputer. The sys
-tem has a back-propaga
-tion **learning** rate of 1 bil
-lion connection updates
per second.
(503) 690-1236
American NeuralLogix
NLX420: Neural proces
-sor slice. A **digital** chip de
-signed for real-time **neural**
network systems, This 20
-MHz device contains 16 pro
-cessing elements, and can
have up to 64,000 16-bit
synaptic inputs.
(407) 322-5608
Intel
807170NX ETANN: An elec
-trically **trainable** analog
neural **network** chip. One
chip can perform over 2 bil
-lion multiply-accumulate
operations per second
(408) 765-9235
Neural
Semiconductor
CNU3232: **Digital** neural

net chip implements a sin
-gle-layer network of 32 in
-puts and 32...

...cmos It has a forward pro
-cess of 3 billion connections
per second and a **learning**
speed of 1.5 billion connec
-tions per second.
(408) 432-8800
Synaptics
I-1000: Analog **neural**
network chip designed spe
-cifically for reading checks.
A **neural** **network** -based im
-age sensor reads the **image**
and a **neural** **network**
trained to recognize the
characters on a check inter
-prets them.
(408) 434-0110

DESCRIPTORS: **Neural** **Network** ; ...

... **Artificial** **Intelligence** ;
19921000

```
Set     Items   Description
S1      36989   AU=(ZHANG H? OR ZHANG, H?)
S2        333   AU=(CARLS G? OR CARLS, G? OR GUBERMAN S? OR GUBERMAN, S?)
S3         50   ZHANG(2N)HONG?
S4          0   CARLS(2N)(GARRY OR GARY) OR GUBERMAN(2N)(SHELIA OR SHELIJA
             OR SHEILA OR SHEILJA)
S5      14832   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S6        111   S1:S4 AND S5
S7         35   S6 AND PY<2003
S8         18   RD (unique items)
? show files
File   2:INSPEC 1969-2005/May W3
         (c) 2005 Institution of Electrical Engineers
File   6:NTIS 1964-2005/May W3
         (c) 2005 NTIS, Intl Cpyrght All Rights Res
File   8:Ei Compendex(R) 1970-2005/May W3
         (c) 2005 Elsevier Eng.  Info. Inc.
File  34:SciSearch(R) Cited Ref Sci 1990-2005/May W4
         (c) 2005 Inst for Sci Info
File  35:Dissertation Abs Online 1861-2005/May
         (c) 2005 ProQuest Info&Learning
File  62:SPIN(R) 1975-2005/Mar W2
         (c) 2005 American Institute of Physics
File  65:Inside Conferences 1993-2005/May W4
         (c) 2005 BLDSC all rts. reserv.
File  94:JICST-EPlus 1985-2005/Apr W1
         (c)2005 Japan Science and Tech Corp(JST)
File  95:TEME-Technology & Management 1989-2005/Apr W3
         (c) 2005 FIZ TECHNIK
File  99:Wilson Appl. Sci & Tech Abs 1983-2005/Apr
         (c) 2005 The HW Wilson Co.
File 111:TGG Natl.Newspaper Index(SM) 1979-2005/May 26
         (c) 2005 The Gale Group
File 144:Pascal 1973-2005/May W3
         (c) 2005 INIST/CNRS
File 256:TecInfoSource 82-2005/Apr
         (c) 2005 Info.Sources Inc
File 434:SciSearch(R) Cited Ref Sci 1974-1989/Dec
         (c) 1998 Inst for Sci Info
?
```

8/3,K/4 (Item 4 from file: 2)
DIALOG(R)File 2:INSPEC

7348288 INSPEC Abstract Number: C2002-09-5260B-234
Title: 3D object recognition for autonomous mobile robots utilizing support vector **classifiers**
Author(s): Schwenker, F.; Kestler, H.A.; Simon, S.; Palm, G.
Author Affiliation: Dept. of Neural Inf. Process., Ulm Univ., Germany
Conference Title: Proceedings 2001 IEEE International Symposium on Computational Intelligence in Robotics and Automation (Cat. No.01EX515) p.344-9
Editor(s): Zhang, H.
Publisher: IEEE, Piscataway, NJ, USA
Publication Date: 2001 Country of Publication: USA xiii+560 pp.
ISBN: 0 7803 7203 4 Material Identity Number: XX-2001-02240
U.S. Copyright Clearance Center Code: 0-7803-7203-4/01/$10.00
Conference Title: Proceedings of 2001 International Symposium on Computational Intelligence in Robotics and Automation
Conference Sponsor: IEEE Robotics & Autom. Soc
Conference Date: 29 July-1 Aug. 2001 Conference Location: Banff, Alta., Canada
Language: English
Subfile: C
Copyright 2002, IEE
Title: 3D object recognition for autonomous mobile robots utilizing support vector **classifiers**
...Abstract: localisation in the camera images, feature extraction, and classification of the extracted feature vectors with **support vector** networks.
Identifiers: **support vector machines ;**
Zhang, H. (editor) 2001

8/3,K/10 (Item 5 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

06087894 E.I. No: EIP02287011050
Title: Motion pattern based video classification using support vector machines
Author: Ma, Yu-Fei; **Zhang, Hong-Jiang**
Corporate Source: Microsoft Research Asia, Beijing, (100080), China
Conference Title: 2002 IEEE International Symposium on Circuits and Systems
Conference Location: Phoenix, AZ, United States Conference Date: 20020526-20020529
E.I. Conference No.: 59248
Source: Proceedings - IEEE International Symposium on Circuits and Systems v 2 2002. p II/69-II/72 (IEEE cat n 02ch37353)
Publication Year: 2002
CODEN: PICSDI ISSN: 0271-4310
Language: English

Title: Motion pattern based video classification using support vector machines
Author: Ma, Yu-Fei; **Zhang, Hong-Jiang**
...Abstract: motion pattern descriptor, which can be extracted from shots or video clips. By using kernel **support vector machines** (SVMs), we have devised an optimized multi-class classifier to link low level features with...
Identifiers: Motion pattern based video classification; **Support vector machines** ; Motion texture; Semantic classification scheme

8/3,K/12 (Item 7 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

05996508 E.I. No: EIP02046840769
Title: Learning probabilistic distribution model for multi-view face detection
Author: Gu, Lie; Li, Stan Z.; **Zhang, Hong-Jiang**
Corporate Source: Microsoft Research China, Beijing 100080, China
Conference Title: 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition
Conference Location: Kauai, HI, United States Conference Date: 20011208-20011214
E.I. Conference No.: 58975
Source: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition v 2 2001. p II116-II122 (IEEE cat n PR01272)
Publication Year: 2001
CODEN: PIVRE9 ISSN: 1063-6919
Language: English

Author: Gu, Lie; Li, Stan Z.; **Zhang, Hong-Jiang**
...Abstract: one of the view classes or into the nonface cls, by using a multi-class **SVM** array classifier. The classification results from each view are fused together and yields the final...

8/3,K/13 (Item 8 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

05916031 E.I. No: EIP01436696807
Title: Distance-from-boundary as a metric for texture image retrieval
Author: Guo, G.; **Zhang, H.-J.** ; Li, S.Z.
Corporate Source: Microsoft Research China, Beijing 100080, China
Conference Title: 2001 IEEE Interntional Conference on Acoustics, Speech, and Signal Processing
Conference Location: Salt Lake, UT, United States Conference Date: 20010507-20010511
E.I. Conference No.: 58543
Source: ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings v 3 2001. p 1629-1632 (IEEE cat n 01CH37221)
Publication Year: 2001
CODEN: IPRODJ ISSN: 0736-7791
Language: English

Author: Guo, G.; **Zhang, H.-J.** ; Li, S.Z.
...Abstract: performance can be improved. The boundaries are obtained by using a statistical learning algorithm called **support vector machine** (**SVM**), and hence the boundaries can be simply represented by some vectors and their combination coefficients...
Identifiers: Texture image retrieval; Distance from boundary; Texture indexing; **Support vector machines** ; Learning similarity

8/3,K/14 (Item 9 from file: 8)
DIALOG(R)File 8:Ei Compendex(R)

05900345 E.I. No: EIP01416673817
Title: Kernel machine based learning for multi-view face detection and pose estimation
Author: Li, S.Z.; Fu, Q.D.; Gu, L.; Scholkopf, B.; Cheng, Y.; **Zhang, H.**
Corporate Source: Microsoft Research China Beijing Sigma Center, Beijing 100080, China
Conference Title: 8th International Conference on Computer Vision
Conference Location: Vancouver, BC, United States Conference Date: 20010709-20010712
E.I. Conference No.: 58404
Source: Proceedings of the IEEE International Conference on Computer Vision v 2 2001. p 674-679
Publication Year: 2001
CODEN: PICVES
Language: English

Author: Li, S.Z.; Fu, Q.D.; Gu, L.; Scholkopf, B.; Cheng, Y.; **Zhang, H.**
...Abstract: of the facial views or into the nonface class, by using a multi-class kernel **support vector** classifier (KSVC). Experimental results show that fusion of evidences from multi-views can produce better ...

8/3,K/18 **(Item 1 from file: 65)**
DIALOG(R)File 65:Inside Conferences

03562342 INSIDE CONFERENCE ITEM ID: CN037518505
GACV for Support Vector Machines
Wahba, G.; Lin, Y.; **Zhang, H.**
CONFERENCE: Large margins-Workshop
P: 297-310
Cambridge, Mass., MIT Press, **2000**
ISBN: 0262194481
LANGUAGE: English DOCUMENT TYPE: Conference Papers
CONFERENCE EDITOR(S): Smola, A. J.
CONFERENCE LOCATION: Breckenridge, CO 1998; Dec (199812) (199812)
NOTE:
Held at the Annual Neural Information Processing Systems conference

GACV for Support Vector Machines
Wahba, G.; Lin, Y.; **Zhang, H.**
Cambridge, Mass., MIT Press, **2000**

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Set      Items   Description
S1        2713   AU=(ZHANG H? OR ZHANG, H?)
S2          28   AU=(CARLS G? OR CARLS, G? OR GUBERMAN S? OR GUBERMAN, S?)
S3         867   ZHANG(2N)HONG?
S4          51   CARLS(2N)(GARRY OR GARY) OR GUBERMAN(2N)(SHELIA OR SHELIJA
              OR SHEILA OR SHEILJA)
S5        4792   SVM OR SUPPORT()VECTOR? OR VECTOR()MACHINE?
S6           6   S1:S4 AND S5
S7           2   S6 AND PY<2003
S8           2   RD (unique items)
? show files
File   9:Business & Industry(R) Jul/1994-2005/May 26
         (c) 2005  The Gale Group
File  13:BAMP 2005/May W3
         (c) 2005  The Gale Group
File  15:ABI/Inform(R) 1971-2005/May 26
         (c) 2005 ProQuest Info&Learning
File  16:Gale Group PROMT(R) 1990-2005/May 26
         (c) 2005 The Gale Group
File  47:Gale Group Magazine DB(TM) 1959-2005/May 27
         (c) 2005 The Gale group
File  75:TGG Management Contents(R) 86-2005/May W3
         (c) 2005 The Gale Group
File  88:Gale Group Business A.R.T.S. 1976-2005/May 26
         (c) 2005 The Gale Group
File  98:General Sci Abs/Full-Text 1984-2004/Dec
         (c) 2005 The HW Wilson Co.
File 141:Readers Guide 1983-2005/Dec
         (c) 2005 The HW Wilson Co
File 148:Gale Group Trade & Industry DB 1976-2005/May 27
         (c)2005 The Gale Group
File 160:Gale Group PROMT(R) 1972-1989
         (c) 1999 The Gale Group
File 239:Mathsci 1940-2005/Jun
         (c) 2005 American Mathematical Society
File 275:Gale Group Computer DB(TM) 1983-2005/May 27
         (c) 2005 The Gale Group
File 369:New Scientist 1994-2005/Apr W2
         (c) 2005 Reed Business Information Ltd.
File 370:Science 1996-1999/Jul W3
         (c) 1999 AAAS
File 484:Periodical Abs Plustext 1986-2005/May W4
         (c) 2005 ProQuest
File 553:Wilson Bus. Abs. FullText 1982-2004/Dec
         (c) 2005 The HW Wilson Co
File 610:Business Wire 1999-2005/May 27
         (c) 2005 Business Wire.
File 613:PR Newswire 1999-2005/May 27
         (c) 2005 PR Newswire Association Inc
File 621:Gale Group New Prod.Annou.(R) 1985-2005/May 27
         (c) 2005 The Gale Group
File 624:McGraw-Hill Publications 1985-2005/May 26
         (c) 2005 McGraw-Hill Co. Inc
File 634:San Jose Mercury  Jun 1985-2005/May 25
         (c) 2005 San Jose Mercury News
File 635:Business Dateline(R) 1985-2005/May 26
         (c) 2005 ProQuest Info&Learning
File 636:Gale Group Newsletter DB(TM) 1987-2005/May 27
         (c) 2005 The Gale Group
File 647:CMP  Computer Fulltext 1988-2005/May W1
         (c) 2005 CMP Media, LLC
```

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File 674:Computer News Fulltext 1989-2005/May W3
         (c) 2005 IDG Communications
File 696:DIALOG Telecom. Newsletters 1995-2005/May 26
         (c) 2005 The Dialog Corp.
File 810:Business Wire 1986-1999/Feb 28
         (c) 1999 Business Wire
File 813:PR Newswire 1987-1999/Apr 30
         (c) 1999 PR Newswire Association Inc
?
```

8/3,K/1 (Item 1 from file: 88)
DIALOG(R)File 88:Gale Group Business A.R.T.S.

06224095 SUPPLIER NUMBER: 90469748
Learning similarity measure for natural image retrieval with relevance feedback.(Abstract)
Guo, Guo-Dong; Jain, Anil K.; Ma, Wei-Ying; **Zhang, Hong-Jiang**
IEEE Transactions on Neural Networks, 13, 4, 811(10)
July, 2002
DOCUMENT TYPE: Abstract ISSN: 1045-9227 LANGUAGE: English
RECORD TYPE: Abstract

... **Zhang, Hong-Jiang**

...AUTHOR ABSTRACT: images, but also significantly improves the retrieval performance of the Euclidean distance measure. Two techniques, **support vector machine (SVM)** and AdaBoost from machine learning, are utilized to learn the boundary. They are compared to...

...Index Terms--AdaBoost, constrained similarity measure, content-based image retrieval, feature selection, learning, relevance feedback, **support vector. machine (SVM)**.

20020701